

RETAILER BEHAVIOR IN INFORMATION-ENABLED SUPPLY CHAINS:
MODELS, ANALYSIS, AND IMPACT

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This dissertation focuses on how an information-enabled (i.e. there is free flow of demand information from the retailer to the supplier) supply chain utilizes the information about retailer behavior. By understanding, quantifying, and incorporating retailer behavior into the supplier's decision making process, we can significantly improve supplier performance and in some cases, the total supply chain performance as well. The three chapters in this dissertation each deal with a different aspect of retailer behavior and thus result in models that are unique. In each case, a rigorous mathematical analysis coupled with an extensive numerical study enables us to characterize useful managerial insights.

The first chapter analyzes a supplier's inventory-control mechanism and its resulting impact on total supply chain cost using knowledge of the retailer inventory policy and the availability of real-time demand information. When the retailer uses the locally optimal (s,S) policy, there is randomness in order time and order quantity to the supplier whereas the supplier sees randomness only in order quantity for the locally suboptimal (R,T) policy and only in order time for another locally suboptimal (Q,r) policy. We find that the suboptimal policies perform better in most cases from the total supply chain perspective.

The second chapter examines when errors occur during a retailer's information processing. By incorporating knowledge about the presence of these additive errors into an information-sharing model, we analyze how they affect the supply-chain cost. We observe that the detrimental impact of errors outweighs the beneficial impact of information sharing when the variance of errors exceeds the variance of end-customer demands. We further present an analytical model for determining the optimal level of investment to reduce information errors.

The third chapter studies how a supplier, with retailers behaving as human newsvendors, can reduce inventory costs by quantifying and incorporating the retailers' behavioral tendencies such as mean-anchoring and/or demand-chasing into the decision making processes. We develop mathematical models to estimate each retailer's order quantity in the presence of these behavioral tendencies. We observe that the supplier's inventory costs can be reduced significantly by considering this aspect of retailer behavior.

BIOGRAPHICAL SKETCH

Jin Kyung Kwak was born on May 30, 1980 in Seoul, Korea, the daughter of Keun Kwak and Young-ae Kim. Jin Kyung graduated from Han Young Foreign Language High School and received her Bachelor's and Master's degrees in Business Administration from Seoul National University in Korea. She joined the Johnson Graduate School of Business at Cornell University for PhD study and met her husband, Oukjae Lee, a PhD student in Applied Physics at Cornell University at that time. They got married in 2010 and a year later, their daughter, Diane Lee, was born on the Valentine's Day. Jin Kyung earns the doctoral degree in summer 2012.

To my parents

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CHAPTER 1

**RETAILER POLICY, UNCERTAINTY REDUCTION,
AND SUPPLY CHAIN PERFORMANCE**

1.1. Introduction

In this information age, competition for businesses is fierce, and firms cannot stay competitive by focusing solely on their individual profits. The emphasis must be on the performance of the whole supply chain. The supply chain that meets the ever-changing customer needs in a timely manner at a lower cost will eventually be dominant. Researchers have argued that sharing information with other members in the supply chain is a way to achieve and maintain this competitive edge. Specifically, as explained in Lee et al. (1997) and Chen et al. (1999), sharing demand information among supply chain members lessens the bullwhip effect (a phenomenon in which distorted demand information leads to amplified upstream order variability), which is one of the major causes of supply chain inefficiency. Lee et al. (2000) showed how a manufacturer in a two-stage supply chain can reduce inventory and lower costs when the retailer provides the end-customer demand information. These savings due to information sharing can vary quite a bit depending on the supply chain structure, parameters, and operating policies (See Gavirneni et al. (1999), Gavirneni (2002) and the references therein).

Considering that the cooperative efforts such as information sharing aim for the total supply chain performance, and not just for individual profits; it is an important challenge to look for a desirable supply chain configuration that meets this purpose. In

this chapter, we seek desirable retailer inventory replenishment policies for a supply chain. Which inventory policies are more conducive to information sharing? In fact, inventory policies have drawn the attention of other researchers as well though their focuses are different from ours. Kull and Closs (2008) pointed out that the inventory policy parameters are one of the components that can be changed to achieve supply chain improvement. Moses and Seshadri (2000) explored policy mechanisms that are simultaneously beneficial to the supplier and the retailer. Kelle and Milne (1999) investigated how the parameters of an (s,S) policy influence the variability of the retailer orders. Our research investigates how changing the operating policies in a supply chain improves the benefit of information sharing and provides an insight about the possibility that locally suboptimal policies may be advantageous to make the best use of information flows.

For a two-stage serial supply chain under periodic review, three well-known retailer inventory policies are considered: An (s,S) policy, an (R,T) policy, and a (Q,r) policy. If a retailer adopts an (s,S) policy, she orders up to S whenever her inventory level reaches or falls below s . On the other hand, if a retailer uses an (R,T) policy, she orders up to R every T^{th} period. Finally, if a retailer follows a (Q,r) policy, she orders the fixed amount of Q whenever her inventory level reaches or falls below r . Scarf (1960) proved that the (s,S) policy is optimal for a retailer under periodic inventory review when there is a fixed setup cost at the retailer. In such a case, it is interesting to review the motivation for comparing the optimal (s,S) policy to the locally suboptimal (R,T) or (Q,r) policies. Notice that when the retailer follows an (s,S) policy, the supplier faces randomness in order time as well as order quantity. However, the

supplier sees randomness (probably larger than the one in the (s,S) setting) only in order quantity when the retailer uses an (R,T) policy and only in order time when the retailer uses a (Q,r) policy. Therefore, by comparing these three circumstances, we obtain some knowledge about how the entire supply chain costs are affected in terms of uncertainty. The basic idea is to study whether the supplier's savings from reduced uncertainty may exceed the retailer's loss from using a suboptimal policy. The answer is not obvious and has implications on which policy is better for the entire supply chain to pursue in the presence of information sharing.

The efforts to improve a supply chain by reducing uncertainties have been attempted in many papers. For example, Chidderhouse and Towill (2004) analyze how the uncertainty reduction correlates with the supply chain performance by classifying the sources of uncertainty into four categories: process side, supply side, demand side, and control side. In fact, information sharing is also one of the uncertainty reduction efforts because it aims for reducing demand uncertainty faced by the supplier (demand side). An (R,T) policy can be said to target more reliable shipment by reducing uncertainty in order time (process side) and a (Q,r) policy aims to reduce uncertainty in order quantity to the supplier (supply side). Many other papers also identify the sources of uncertainty and emphasize that supply chain management should be concerned with uncertainty reduction to improve the performance of the chain, theoretically (Chopra and Sodhi (2004), Christopher and Lee (2004), Ganguly and Guin (2007), etc.) or by case studies (Van der Vorst et al. (1998), Boyle et al. (2008)). This study is different from those existing papers as its focus lies in inventory control, specifically studying how changing the retailer inventory policy can reduce

uncertainties faced by the supplier which in turn affects total supply chain costs with or without information sharing.

Using a two-stage serial supply chain (with a fixed ordering cost at the retailer) as our basic setting, we address the following issues: (i) what is the structure of optimal policies for the supplier under the retailer's different inventory policies? (ii) which policy at the retailer will be better for the entire supply chain? and (iii) what parameter settings play a key role in making the suboptimal policies more beneficial for a supply chain? It is expected that answering these research questions will help to generate managerial suggestions on when and how to reduce uncertainties in inventory management for a supply chain in practice.

By undertaking extensive computational experiments, we find that, in most cases, it is better for the retailer to use (R,T) or (Q,r) policies than to use the locally optimal (s,S) policy for the sake of the total supply chain. The benefit from using suboptimal policies is magnified when the retailer costs are low, when the supplier costs are high, and when there is information sharing. An (R,T) policy is more effective for lower demand variability while a (Q,r) policy is more effective for higher demand variability. In addition, we analyze the behavior of the benefit from information sharing under the three policies.

The rest of this chapter is organized as follows. In Section 1.2, we introduce the supply chain setup with the models analyzed in this chapter. Section 1.3 explains our computational study and analyzes the benefit of using suboptimal policies instead of the locally optimal (s,S) policy from the total supply chain perspective. Section 1.4

presents the value of information sharing under different policies. In Section 1.5, the effect of capacity and the cases of more demand distributions are studied as extensions. We conclude in Section 1.6 by summarizing our discussions and identifying some directions for future research.

1.2. Models

There are hundreds of papers about information sharing and inventory control in a supply chain addressing various kinds of supply chain settings (See de Kok and Graves (2003)). The models, assumptions, and research methodology in this study follow the lines of Gavirneni et al. (1999) and Gavirneni (2002). We study a two-stage serial supply chain composed of one retailer and one supplier. The supplier produces the items which a retailer orders from him and sells to the end-customers with i.i.d. random demands. There is a fixed ordering cost (K) at the retailer along with unit holding cost (h_r) for excess inventory and unit penalty cost (p_r) for backlogged demands. The supplier incurs unit holding cost (h_s) for excess inventory and unit expediting cost (p_s) for the retailer demand that he cannot satisfy from on-hand inventory. We assume, like Lee et al. (1999), that the supplier uses an expediting process, incurring additional cost to provide the product demanded by the retailer as quickly as possible. There is infinite production capacity at the supplier.

The sequence of events is following. (1) The supplier decides his production quantity for a period. The product is available immediately at his location. (2) The end-customer demand is realized for the period at the retailer. (3) After fully or partially satisfying the demand, the retailer either places an order or does nothing,

according to her inventory replenishment policy. (4) If the retailer places an order, the complete shipment (because, if needed, the supplier expedites) arrives at the beginning of the next period. (5) At the end of each period, the holding or penalty costs are calculated in accordance with the inventory levels. The fixed cost is calculated at the end of the period when the order is placed.

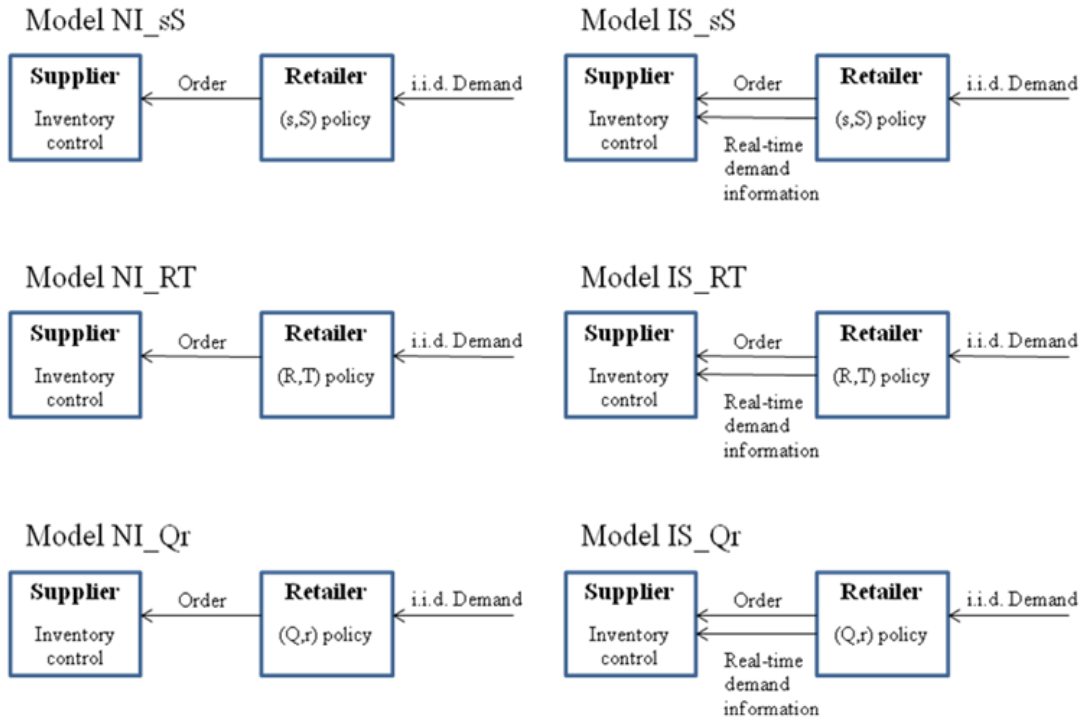


Figure 1.1: Models with different retailer policies

With this setup, we compare the supply chain costs under different policies. Note that the performance measure in this study is the total supply chain cost, not the individual (the retailer or the supplier) costs, to observe the plausible superiority of locally suboptimal policies. Figure 1.1 shows a brief description of the six models we analyze in this study. In the model names, NI refers to “no information sharing” while IS refers to “information sharing.” Information in this context refers to the real-time

information about end-customer demand up until the previous period provided to the supplier by the retailer.

1.2.1. Model NI_sS and Model IS_sS

In Model NI_sS and Model IS_sS, the retailer uses the optimal (s,S) policy. It is a reasonable assumption that the supplier figures out the retailer's (s,S) policy and pursues his own optimal replenishment schemes.

The analysis of these two models is well-documented in Gavirneni et al. (1999). They proved that the supplier's optimal policy in both Model NI_sS and Model IS_sS is a state-dependent order-up-to policy. The state is defined as the number of periods since last order from the retailer for Model NI_sS and as the total end-customer demand seen by the retailer since last order for Model IS_sS. At the beginning of each period, the supplier observes the state and decides his order quantity to make the inventory level reach the optimal order-up-to level for that state. The optimal order-up-to levels can be found by using an IPA (Infinitesimal Perturbation Analysis) procedure. They also established that for the supplier the cost function is convex and the order-up-to levels are non-decreasing in state. These properties are valid for both Model NI_sS and Model IS_sS.

As a result of comparing Model NI_sS and Model IS_sS, they found that information is always beneficial. The savings from information sharing ranged from 1% to 35% with an average of 14%. In addition, they observed the following phenomena: (1) information benefits are highest for moderate ratios of penalty cost to

holding cost; (2) information is most beneficial at moderate values of end-customer demand variance; and (3) information is most valuable for moderate value of (S-s).

1.2.2. Model NI_RT and Model IS_RT

Using similar arguments as in the previous subsection, it can be shown that the supplier's optimal policy for Model NI_RT is a state-dependent order up-to policy as well. The state for Model NI_RT can be defined as the number of periods since last order, the same as in Model NI_sS. This is even simpler because the supplier has to observe the state only at the ordering epoch, once every T^{th} period. At the beginning of each period, the supplier knows whether or not the retailer is going to place an order in that period. With this information, the supplier decides the order quantity to minimize his expected holding and expediting costs. The resulting inventory control problem can be formulated as follows.

t = the index of the period when there are t remaining periods

x_t = the starting inventory in period t

$$y_t = \begin{cases} 0 & \text{no order from the retailer in period } t \\ 1 & \text{order from the retailer in period } t \end{cases}$$

z_t = the order up-to level in period t

D_t = the end-customer demand in period t

$F(\cdot)$ = the distribution of the end-customer demand

R_t = the retailer demand in period t

$$= \begin{cases} 0 & \text{if } y_t = 0 \\ \sum_{t=1}^T D_t & \text{if } y_t = 1 \end{cases}$$

$V_t(x_t, y_t)$ = the supplier cost of the remaining t periods

$$V_t(x_t, y_t) = \begin{cases} h_s x_t^+ + V_{t-1}(x_t, y_{t-1}) & \text{if } y_t = 0 \\ \min_{z_t \geq x_t} E_{R_t} \{h_s (z_t - R_t)^+ + p_s (R_t - z_t)^+ + V_{t-1}(z_t - R_t, y_{t-1})\} & \text{if } y_t = 1 \end{cases}$$

By defining a mega-period as T consecutive periods, the cost function of one mega-period u is:

$$C(z_u) = E_{R_u} [Th_s (z_u - R_u)^+ + p_s (R_u - z_u)^+].$$

The order-up-to level that minimizes this cost function is the newsvendor solution,

$F_T^{-1}(\frac{p_s}{Th_s + p_s})$, where F_T is the T^{th} convolution of the end-customer demand

distribution since the retailer demand for every T^{th} period is the sum of the end-customer demand over T periods.

Similarly to Model NI_RT, the supplier's inventory control problem for Model IS_RT can be formulated as follows with the state defined as the total end-customer demand seen by the retailer since last order.

∇_t = the cumulative end-customer demand, in period t , realized at the retailer since her last order

$V_t(x_t, y_t, \nabla_t)$ = the supplier cost of the remaining t periods

$$V_t(x_t, y_t, \nabla_t) = \begin{cases} h_s x_t^+ + V_{t-1}(x_t, y_{t-1}, \nabla_{t-1}) & \text{if } y_t = 0 \\ \min_{z_t \geq x_t} E_{D_t} [h_s \{z_t - (\nabla_t + D_t)\}^+ + p_s \{(\nabla_t + D_t) - z_t\}^+ + V_{t-1}(z_t - (\nabla_t + D_t), y_{t-1}, 0)] & \text{if } y_t = 1 \end{cases}$$

The supplier's optimal order up-to level can be computed, using newsvendor methodology, as $\nabla_t + F^{-1}(\frac{p_s}{Th_s + p_s})$. Notice that the critical fractile is applied directly to the end-customer demand distribution and not its convolution because there is uncertainty only in one-period demand.

Unlike the case under an (s,S) policy, we are able to analytically characterize the benefit of information sharing under an (R,T) policy if we suppose the end customer demand is normally distributed with mean μ and variance σ^2 . The supplier's optimal order-up-to levels can be restated as

$$F_T^{-1}(\frac{p_s}{Th_s + p_s}) = T\mu + z\sqrt{T}\sigma \quad \text{for Model NI_RT ; and}$$

$$\nabla_t + F^{-1}(\frac{p_s}{Th_s + p_s}) = \nabla_t + \mu + z\sigma \quad \text{for Model IS_RT}$$

where $z = \Phi^{-1}\left(\frac{p_s}{Th_s + p_s}\right)$. By Hadley and Whitin (1963), the cost of using this base

stock policy can be calculated as:

$$C_{NI} = \frac{1}{T} \sqrt{T}\sigma(Th_s + p_s)\phi(z),$$

$$C_{IS} = \frac{1}{T} \sigma(Th_s + p_s)\phi(z)$$

where C_{NI} = the supplier cost of Model NI_RT, and

C_{IS} = the supplier cost of Model IS_RT.

The supplier cost of Model IS_RT is always lower (better) than that of Model NI_RT. Therefore, sharing demand information is always beneficial to the supplier when the retailer uses an (R,T) policy. Additionally, we can observe that the relative cost benefit to the supplier increases as the order time T increases and is independent of demand variance.

1.2.3. Model NI_Qr and Model IS_Qr

When the retailer uses a (Q,r) inventory policy, the supplier will observe that the retailer orders either the fixed amount Q or nothing. To pursue the supplier's optimal inventory control we define a state for Model NI_Qr as

i = the number of periods that have elapsed since last order.

Suppose p_i denotes the probability that the retailer will place an order after i periods. Then the retailer order, R_i , faced by the supplier for each state i is either Q with probability p_i or 0 with probability $(1 - p_i)$. Note that $p_i \leq p_{i+1}$. The optimization problem to calculate the supplier's order-up-to level z_i can be expressed as

$$\min E_{R_i} [h_s (z_i - R_i)^+ + p_s (R_i - z_i)^+] \quad \text{for each state } i.$$

As a result, the supplier's optimal order-up-to level for each state is calculated as follows:

$$z_i = \begin{cases} Q & \text{if } p_i \geq \frac{h_s}{h_s + p_s} \\ 0 & \text{if } p_i < \frac{h_s}{h_s + p_s} \end{cases}.$$

For Model IS_Qr, we define a new state i as

i = the retailer's inventory level observed by the supplier.

As the supplier gains the demand information provided by the retailer, he can detect the retailer's inventory level each period. In this case, let p_i denote the probability that the retailer will place an order when the retailer's inventory level is i . That is,

$$p_i = \Pr(D_i \geq i - r), \text{ and it is shown that } p_i \geq p_{i+1}.$$

Similarly to Model NI_Qr, the supplier's optimal order-up-to level for Model IS_Qr is calculated as follows:

$$z_i = \begin{cases} Q & \text{if } i \leq F^{-1}\left(\frac{p_s}{h_s + p_s}\right) + r \\ 0 & \text{if } i > F^{-1}\left(\frac{p_s}{h_s + p_s}\right) + r \end{cases}$$

where $F(\cdot)$ is the demand distribution function.

The benefit of information sharing under a (Q,r) policy that can be evaluated by comparing Model NI_Qr and Model IS_Qr will be detailed in Section 1.4 through a computational study.

1.3. Benefit of uncertainty reduction

Based on the structures of inventory policies established in Section 1.2, we want to perform, using an extensive numerical study, a rigorous investigation into how various supply chain parameters affect the possible benefit of suboptimal (R,T) and (Q,r)

policies over an (s,S) policy. Because of the difficulty in obtaining the costs (especially for (s,S) and (Q,r) policies) analytically, the supply chain behavior can only be observed via simulation.

Infinitesimal Perturbation Analysis (IPA) is used to find the optimal (R,T) values for the retailer and the optimal order up-to levels for the supplier. (Refer to Glasserman and Tayur (1995) for more details on the IPA procedure.) To find the optimal (s,S) values for the retailer, we use the algorithm developed by Zheng and Federgruen (1991). To compute the optimal (R,T) values for the retailer, we first determine the optimal value of R given T (Rao (2003)). By comparing the cost of each (R,T) policy for different values of T , we acquire the optimal (R,T) values. For (Q,r) cases, we develop a program to find optimal (Q,r) values with initial values $Q = S - s$ and $r = s$. For (s,S) and (R,T) models, the above-mentioned IPA procedure is used to compute the supplier's order-up-to levels and for (Q,r) models, the supplier's order-up-to level is either Q or 0 .

The goal of this computational study is to compare the supply chain costs under different policies in order to explore the role of uncertainty reduction with or without information sharing. Remember that the performance measure is the entire supply chain cost, but neither the retailer cost nor the supplier cost. The number of the simulated periods is 1,000,000 times the optimal T value, which we found is enough to guarantee infinite-horizon average costs.

1.3.1. Computational setup

The simulation experiments were conducted with the following parameters which constitute 625 combinations for each demand distribution: $h_r = 1$ for all the experiments; $p_r = \{3,5,7,9,11\}$; $h_s = \{0.5,0.7,0.9,1.1,1.3\}$; $p_s = \{3,5,7,9,11\}$; and $K = \{30,50,70,90,110\}$. We consider three demand distributions: Erlang (2,10), Erlang (4,5), and Erlang (8, 2.5). Erlang distributions are selected as they generate non-negative demands and enable us to compare demand distributions with the same mean (20) but various levels of uncertainty: cv (coefficient of variation) of Erlang (2,10) = 0.71; cv of Erlang (4,5) = 0.5; and cv of Erlang (8,2.5) = 0.35.

Random examples are taken to show how the numerical study works:

Example 1: Erlang (2,10), $h_r = 1$, $p_r = 5$, $h_s = 0.7$, $p_s = 11$, $K = 50$.

Example 2: Erlang (4,5), $h_r = 1$, $p_r = 7$, $h_s = 1.3$, $p_s = 5$, $K = 90$.

Table 1.1. Cost data of two examples

Example	NI_sS			NI_RT			NI_Qr		
	C_R	C_S	C_{SC}	C_R	C_S	C_{SC}	C_R	C_S	C_{SC}
1	49.89	38.80	88.69	59.50	27.93	87.43	51.99	23.28	75.27
2	61.28	35.00	96.28	69.17	20.74	89.91	62.50	32.25	94.75
Example	IS_sS			IS_RT			IS_Qr		
	C_R	C_S	C_{SC}	C_R	C_S	C_{SC}	C_R	C_S	C_{SC}
1	49.89	37.12	87.01	59.50	20.62	80.12	51.99	22.91	74.90
2	61.28	27.57	88.85	69.17	11.66	80.83	62.50	19.87	82.37

Note: C_R = the retailer cost, C_S = the supplier cost, C_{SC} = the total supply chain cost

Table 1.1 illustrates the detailed cost data for these examples. As expected, (s,S) models have the lowest retailer cost because an (s,S) policy is optimal for the retailer

and the supplier costs of (R,T) and (Q,r) models are lower than that of (s,S) models as the supplier faces less uncertainty in order time or in order quantity. However, we cannot say which models are always superior to other models since the rank of the total supply chain cost varies depending on demand distribution, cost parameters, and availability of information. Another observation is that the supplier benefits from information sharing.

1.3.2. Results and implications

The computational setup generates a total of 1875 cases. When there is no information sharing, the supply chain cost of (R,T) model is smaller than that of (s,S) model in 76.48% of the cases and the supply chain cost of (Q,r) model is smaller than that of (s,S) model in 85.23% of the cases. When there is information sharing, the benefit of the retailer using suboptimal policies to reduce uncertainty faced by the supplier is more pronounced: in 94.08% of the cases, the supply chain cost of (R,T) model is smaller than that of (s,S) model; and in 99.73% of the cases, the supply chain cost of (Q,r) model is smaller than that of (s,S) model. Average percentage benefit gained by switching from an (s,S) policy to different policies is 3.86% for an (R,T) policy with no information sharing, 7.74% for an (R,T) policy with information sharing, 4.81% for a (Q,r) policy with no information sharing, and 8.02% for a (Q,r) policy with information sharing, respectively.

It is noteworthy that (R,T) or (Q,r) policies perform better than the locally optimal (s,S) policy in most cases from the entire supply chain perspective. Obviously, the improvement is achieved by reducing uncertainty faced by the supplier. Under our

computational setting, while the average increase in retailer cost compared to an (s,S) policy is 12.68% for an (R,T) policy and 3.10% for a (Q,r) policy, the average saving in supplier cost compared to an (s,S) policy is 34.70% for an (R,T) policy with no information sharing, 52.42% for an (R,T) policy with information sharing, 18.63% for a (Q,r) policy with no information sharing, and 31.89% for a (Q,r) policy with information sharing. From these results, the uncertainty reduction in order time seems to benefit the supplier more effectively than the uncertainty reduction in order quantity, whereas an (R,T) policy is farther from optimal to the retailer than a (Q,r) policy.

In the following, we plot the average benefit (% savings in total supply chain cost by retailer changing her current (s,S) policy to other policies) by fixing each parameter, in order to investigate the behavior of the benefit from the policy changes with respect to various parameters. We use the following notation to better illustrate our plots:

$$\% \text{ (R,T) benefit (NI)} = \frac{C_{(s,S)}^{NI} - C_{(R,T)}^{NI}}{C_{(s,S)}^{NI}} \times 100 (\%),$$

$$\% \text{ (R,T) benefit (IS)} = \frac{C_{(s,S)}^{IS} - C_{(R,T)}^{IS}}{C_{(s,S)}^{IS}} \times 100 (\%)$$

$$\% \text{ (Q,r) benefit (NI)} = \frac{C_{(s,S)}^{NI} - C_{(Q,r)}^{NI}}{C_{(s,S)}^{NI}} \times 100 (\%), \text{ and}$$

$$\% \text{ (Q,r) benefit (IS)} = \frac{C_{(s,S)}^{IS} - C_{(Q,r)}^{IS}}{C_{(s,S)}^{IS}} \times 100 (\%)$$

where $C_{(s,S)}^{NI}$ = the supply chain cost of Model NI_sS, $C_{(s,S)}^{IS}$ = the supply chain cost of Model IS_sS, $C_{(R,T)}^{NI}$ = the supply chain cost of Model NI_RT, $C_{(R,T)}^{IS}$ = the supply chain cost of Model IS_RT, $C_{(Q,r)}^{NI}$ = the supply chain cost of Model NI_Qr, and $C_{(Q,r)}^{IS}$ = the supply chain cost of Model IS_Qr.

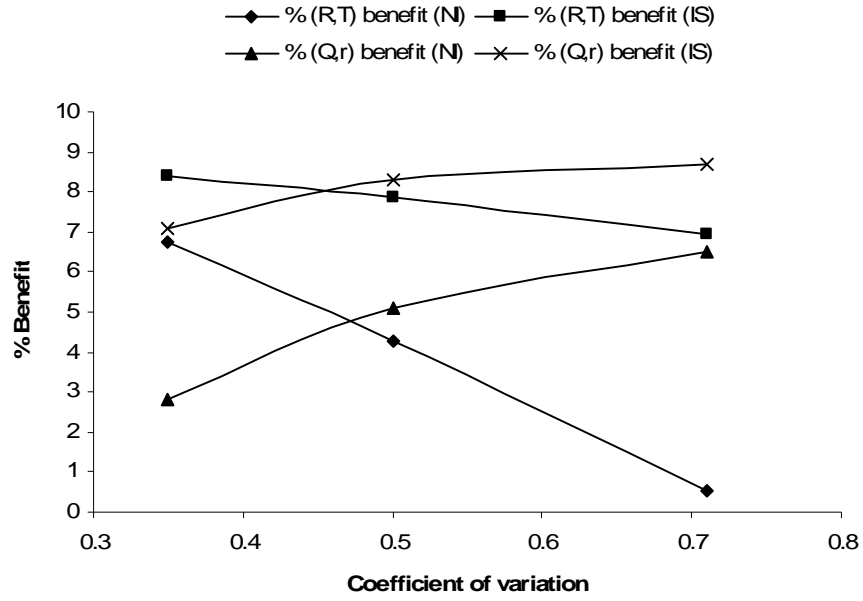


Figure 1.2: Average benefit from policy changes with respect to demand variability

Figure 1.2 shows how the demand variability affects the benefit from the policy changes. Interestingly, an (R,T) policy is more beneficial to the supply chain when the end-customer demand is less variable, whereas a (Q,r) policy is more beneficial when the demand is more variable. This implies that the results could be quite different if we take a certain set of demand distributions: e.g. an (R,T) policy may be always superior to a (Q,r) policy if we only consider the demand distributions with very low variability.

Furthermore, this finding gives us an important insight about the relationship between the demand variability and the role of uncertainty reduction in inventory control. That is, when end-customer demands are highly variable, knowing the exact retailer order amount (if there is an order placement) helps the supplier more than knowing the retailer order frequency. On the other hand, when demand variability is low, the supplier's knowledge of the retailer order frequency is more powerful.

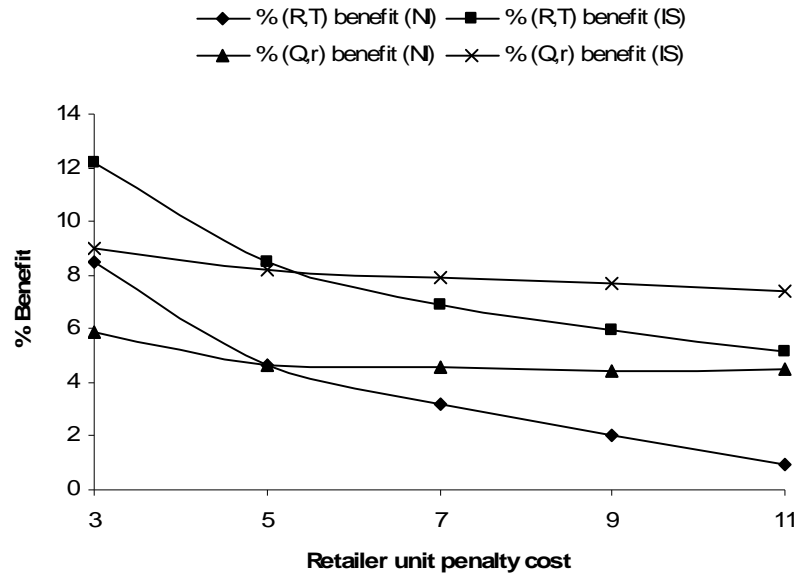


Figure 1.3: Average benefit from policy changes w.r.t. retailer unit penalty cost

Figures 1.3, 1.4, and 1.5 show the increasing or decreasing tendency of the average benefit from policy changes with respect to cost parameters. As the retailer unit penalty cost increases, the advantage of using an (s,S) policy which is optimal to the retailer also increases relatively. Therefore, the benefit of using (R,T) or (Q,r) policies over an (s,S) policy is decreasing in the retailer-associated cost. Retailer's using (R,T) or (Q,r) policies reduces the uncertainty faced by the supplier, thus reducing the

possibility of overstock or stockout at the supplier. Therefore, the relative benefit from the policy changes increases as the supplier-associated cost increases.

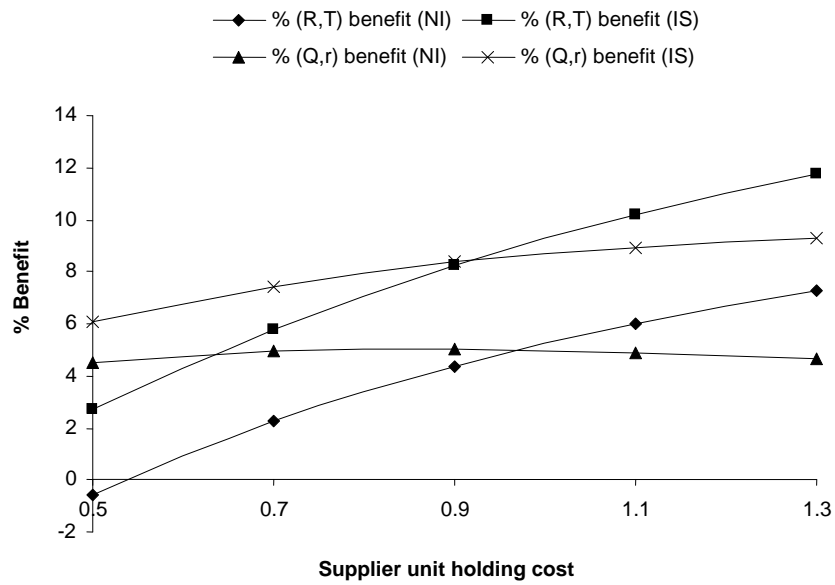


Figure 1.4: Average benefit from policy changes w.r.t. supplier unit holding cost

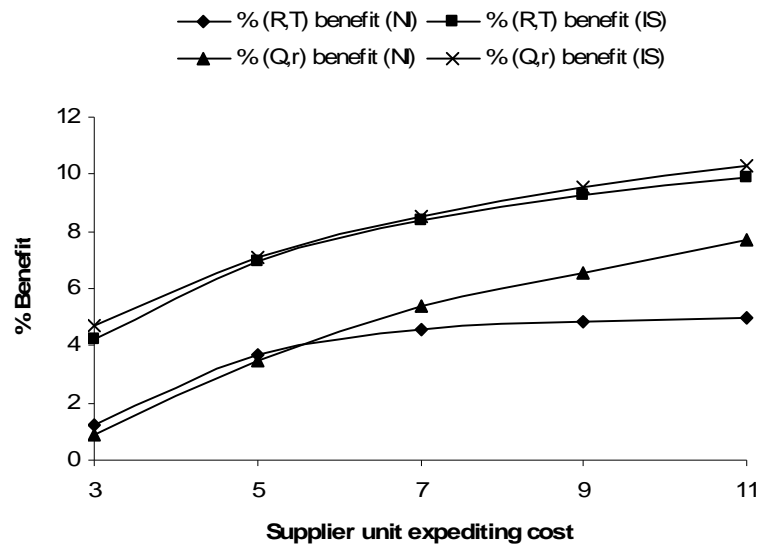


Figure 1.5: Average benefit from policy changes w.r.t. supplier unit expediting cost

1.4. Value of information sharing

By analyzing value of information sharing in this study's setting, not only can we compare the value of information under different policies (three most well-known policies) but also it is possible to validate the accuracy of our computational study. The results about the value of information under an (s,S) policy are actually very similar to those in Gavirneni et al. (1999). Under our computational setting, information is always beneficial to the supplier for all three policies: the relative benefit (cost savings) from information sharing is, on average, 15.39% for an (s,S) policy, 38.19% for an (R,T) policy, and 27.98% for a (Q,r) policy, respectively.

The following measures are defined to analyze the behavior of the benefit from information sharing:

$$\% \text{ Info Benefit (s,S)} = \frac{C_{(s,S)}^{NI} - C_{(s,S)}^{IS}}{C_{(s,S)}^{NI}} \times 100 (\%),$$

$$\% \text{ Info Benefit(R,T)} = \frac{C_{(R,T)}^{NI} - C_{(R,T)}^{IS}}{C_{(R,T)}^{NI}} \times 100 (\%), \text{ and}$$

$$\% \text{ Info Benefit (Q,r)} = \frac{C_{(Q,r)}^{NI} - C_{(Q,r)}^{IS}}{C_{(Q,r)}^{NI}} \times 100 (\%).$$

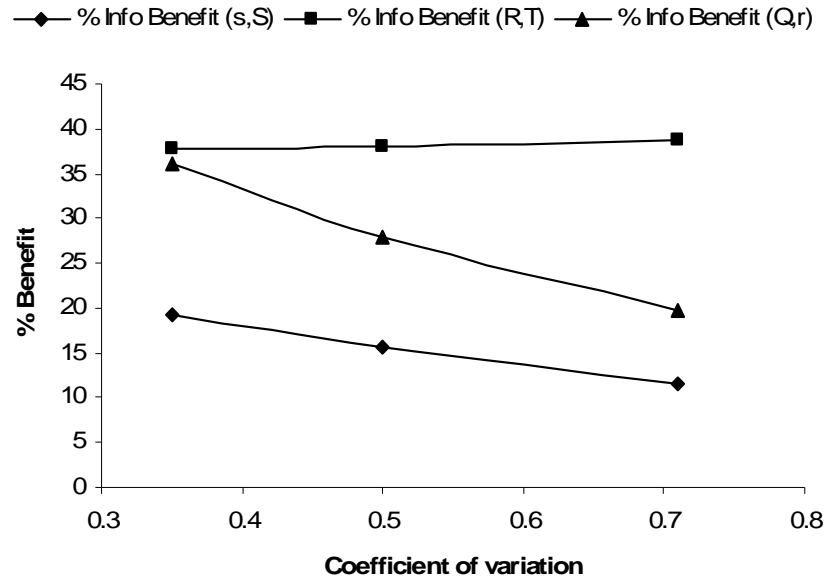


Figure 1.6: Average benefit from information sharing w.r.t. demand variability

Figure 1.6 plots average benefit from information sharing under each policy with respect to coefficient of variation of end customer demand. For (s,S) and (Q,r) policies, the average percentage benefit from information sharing decreases as demand variability increases. As Gavirneni et al. (1999) explained, when the variance is very high, the information to reduce demand uncertainty at the supplier is relatively not effective. On the other hand, the average percentage benefit from information sharing appears to be constant for an (R,T) policy, which is in line with the analytical property (Refer to Section 1.2.2.) that the relative value of information is independent of demand variability for normal demand distribution.

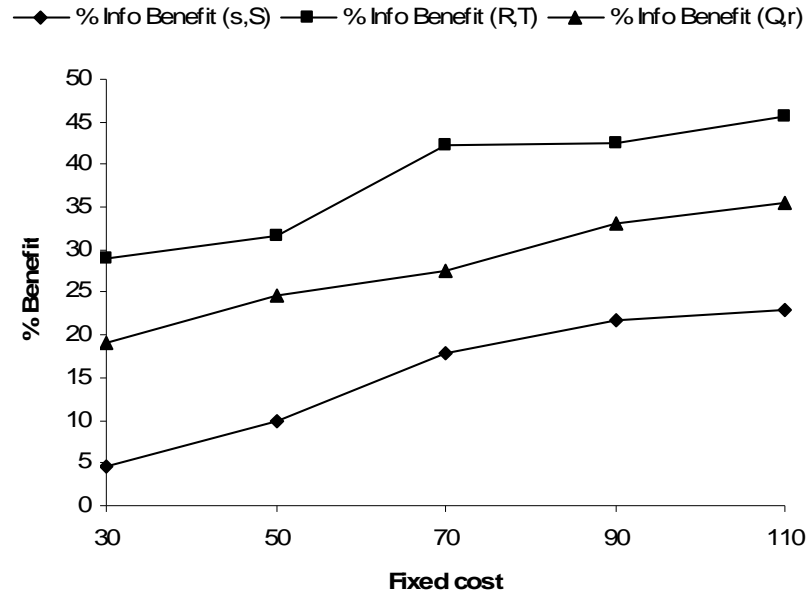


Figure 1.7: Average benefit from information sharing w.r.t. fixed cost

Figure 1.7 shows that average benefit from information sharing is increasing in the fixed cost at the retailer under all three policies. As the fixed cost determines the order interval, these patterns are highly correlated with the order frequency. Remember that the value of information increases with the order time T under an (R,T) policy for normal demand distribution (Refer to Section 1.2.2.). Since the supplier obtains the information of realized demand for $(T-1)$ periods, the relative benefit increases as the order time T increases. Also, for (s,S) and (Q,r) policies, higher fixed cost leads to longer average order interval, i.e. more uncertainty in order time, and so sharing demand information is relatively more effective.

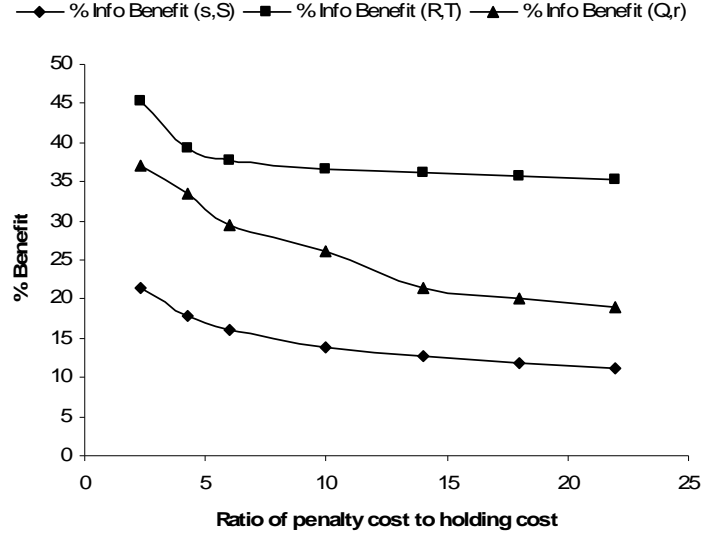


Figure 1.8: Average benefit from info sharing w.r.t. ratio of penalty to holding cost

Figure 1.8 illustrates the average benefit from information sharing with respect to ratio of the supplier unit penalty cost (p_s) to the supplier unit holding cost (h_s). As Gavirneni et al. (1999) stated, information would have very limited benefit if the ratio is close to 0 or is very large. Information is more beneficial for moderate ratios and the peak is reached at a small penalty for all three policies under our computational setting.

1.5. Extensions

In this section, several additional issues regarding the results are addressed. Relaxing some of our previous assumptions facilitates further understanding of how uncertainty reduction by changing a retailer policy affects the supply chain performance. Specifically, we discuss the effects of the supplier's production capacity and various end-customer demand distributions.

1.5.1. Effect of capacity

If there is a capacity limit on suppliers' production, suppliers may need to stock up in advance to meet the retailer demand. This increases the supplier's inventory costs: holding costs increase due to previously-produced stocks and penalty cost may increase due to insufficient inventory caused by a capacity limit. To see how the capacity restriction influences on the benefit of policy changes, we conduct additional experiments with the following computational setup: $K = 30$, $h_r = 1$, and Erlang (4,5) demand for all the experiments; $p_r = \{3,5,7,9,11\}$; $h_s = \{0.5,0.7,0.9,1.1,1.3\}$; $p_s = \{3,5,7,9,11\}$; and capacity limits = $\{20,30,40,50,60,70\}$.

Note that we only consider the cases of no information sharing because our primary interest lies in the effect of capacity, which is not related with information sharing. The results are described in Figure 1.9.

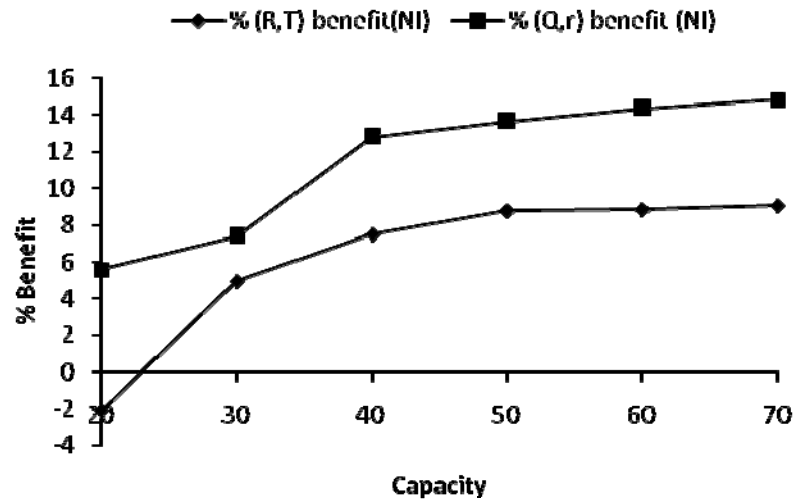


Figure 1.9. Average benefit from policy changes w.r.t. supplier production capacity

It is not so surprising that the results of capacities over 60 are almost the same as those of infinite capacities, considering the values of $(S-s)$ for an (s,S) policy range from 30 to 32, the values of the supplier's order-up-to levels for an (R,T) policy range from 39.52 to 60.92, and the values of Q for a (Q,r) policy range from 32.22 to 49.91, which are determined by the given set of cost parameters. When the supplier's production capacity is below 60, we observe that the average benefit that the supply chain gains from the retailer's changing her inventory policy from an (s,S) policy to an (R,T) policy or a (Q,r) policy is smaller than that of a system where the supplier has infinite capacity. That is, the existence of a capacity limit lessens the advantage of uncertainty reduction to the supplier's inventory control. Remember that when the supplier has an infinite production capacity, the retailer's using an (R,T) policy enables the supplier to produce every T period instead of every period. It would save much of inventory holding costs compared to the capacitated system where the supplier may need to produce beforehand. Likewise, if the supplier's production capacity is less than the value Q of a (Q,r) policy, the benefit of the supplier's preparing for the exact retailer order amount decreases significantly.

1.5.2. More demand distributions

When the end-customer demands follow other types of distributions such as normal, uniform, or exponential distribution, do our results still hold? Here we consider three more distributions with the same mean 20 – Normal $(20,3^2)$ truncated at 0, Uniform $[10,30]$, and Exponential (20) – and conduct extensive simulation experiments with

the same combination of cost parameters as in Section 1.3. Let us assume there is information sharing between supply chain members.

We find out that most of the previous results are valid for these demand distributions as well. First, the retailer's using (R,T) or (Q,r) policies reduces uncertainty to the supplier, leading to the decrease in the supplier's inventory cost. For the total supply chain cost, under Normal $(20,3^2)$ demand distribution, an (R,T) policy performs better than an (s,S) policy in 100% of the cases with 17.34% cost reduction on average and a (Q,r) policy performs better than an (s,S) policy in 66.88% of the cases with 2.82% cost reduction on average. Under Uniform [10,30] demand distribution, an (R,T) policy performs better than an (s,S) policy in 96.96% of the cases with 4.81% cost reduction on average and a (Q,r) policy performs better than an (s,S) policy in 65.6% of the cases with 2.73% cost reduction on average. Under Exponential (20) demand distribution, an (R,T) policy performs better than an (s,S) policy in 76.32% of the cases with 5.17% cost reduction on average and a (Q,r) policy performs better than an (s,S) policy in 86.08% of the cases with 9.15% cost reduction on average.

Second, the relationships between the average benefit (supply-chain cost decrease due to policy changes) and the cost parameters show the same patterns as the results in Section 1.3: The average relative benefit of policy changes decreases with the retailer's unit holding cost (p_r), increases with the supplier's unit holding cost (h_s), and increases with the supplier's unit penalty cost (p_s) under Normal $(20,3^2)$, Uniform [10,30], and Exponential (20) demand distributions.

1.6. Conclusion

This chapter studies the impact of a retailer's inventory policy on the supply chain cost by comparing three well-known inventory policies: (s,S) , (R,T) , and (Q,r) policies. We establish the structure of the supplier's optimal policies depending on the retailer's inventory policy and the availability of demand information. As (R,T) and (Q,r) policies make the supplier face less uncertainty than an (s,S) policy, this study shows how the uncertainty reduction plays an important role in inventory control from a total supply chain perspective.

The numerical results indicate that the retailer using (R,T) or (Q,r) policies is more beneficial to the entire supply chain than an (s,S) policy in most cases. The benefit from policy changes is magnified when the retailer-related cost is low or when the supplier-related cost is high. We can also observe that uncertainty reduction in order time by applying an (R,T) policy is more advantageous for lower demand variability and that uncertainty reduction in order quantity by applying a (Q,r) policy is more advantageous for higher demand variability. In addition, value of information sharing under different policies is analyzed.

An academic contribution of this study is that the well-known three inventory policies are re-evaluated from the total supply chain viewpoint. The finding that the cost saving as a result of reducing uncertainties at the supplier often exceeds the loss to the retailer pursuing non-optimal behaviors is valuable as it is neither obvious nor intuitive at first glance. Further, it is interesting that these sub-optimal but more desirable policies are even easier to implement in practice than a locally optimal but

system-inferior (s,S) policy. If retailers use an (R,T) policy, they do not need to watch inventory levels every single period unlike those who use an (s,S) policy, leading to significant labor savings. For a (Q,r) policy, cost saving due to simplification of transportation is expected since the order amount is fixed. Therefore, the findings of this research also contribute to strategic implications that a change to suboptimal but more practical applications leads to a win-win solution for both retailers and suppliers.

More interestingly, the benefit from policy changes is pronounced when there is information sharing. In other words, uncertainty reduction by changing the retailer policy is one way to enhance the benefit from information sharing. It is an open question what is the best supply chain configuration for information sharing under a certain setting; according to our study, uncertainty reduction will be one of the approaches toward the answer. Future study should explore any other possible approaches.

Identifying an incentive scheme to convince retailers to pursue the proposed sub-optimal policies is another issue worthy of future research. Because only the supplier benefits from the policy changes or from information sharing, we need to find ways to encourage retailers to participate in such efforts for supply chain improvement. Many papers devised means to induce retailers to take part in information sharing. For example, Lee and Whang (1999) study alternative performance mechanisms to align incentives. Yu et al. (2002) propose a strategic partnership between supply chain members by adopting vendor managed inventory (VMI). Likewise, some strategies give retailers incentives to pursue locally suboptimal strategies or supplier can compensate the retailers, possibly via side payments. Any supply chain improvement

endeavors require trust and cooperation between supply chain partners. To search for the methods to attract supply chain cooperation will be another subject that merits future study.

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CHAPTER 2

**IMPACT OF INFORMATION ERRORS
ON SUPPLY CHAIN PERFORMANCE**

2.1. Introduction

Information sharing in supply chains has been a popular research topic and its benefits have been well documented (Chen (1998), Gavirneni et al. (1999), Lee et al. (2000), Chen et al. (2000), Cachon and Fisher (2000), etc.). All these papers have assumed that the shared information is precise and error-free, which, of course, is not true in practice. Enterprise Resource Planning (ERP) systems are known to contain errors that are introduced when inventory recording processes are not followed correctly. Stedman (1998) described the case of a dental equipment maker regarding how those errors can cause problems as follows: incorrect bills of material that were entered for production uses were passed along to inventory managers and left them to believe that the company had more materials than it actually did. In fact, many articles (Stein (1999), Nelson (2002), Umble et al. (2003), Basoglu et al. (2007), etc.) identified information inaccuracy as one of the main reasons for failure of ERP systems. Xu et al. (2002) also underscored the importance of data accuracy in ERP execution by illustrating case studies of two Australian organizations doing SAP projects. As it is usually very expensive to implement ERP systems (Scapens et al. (1998)), it is necessary to ensure their successful implementation. Understanding the impact of information inaccuracy on supply chain performance and ensuring that errors do not lead to a failure must be an important step in any ERP implantation.

The extant research in this area has documented that information errors often originate from retailers. For example, mis-scanning of items, restocking errors or theft may distort inventory information (Raman et al. (2001), BearingPoint (2002), DeHoratius and Raman (2008)). These errors are eventually transmitted to the supplier and impact his inventory management as well, especially if the supplier is not aware of the presence of these errors. The problem of inventory record inaccuracy at retailers is prevalent and empirical evidence suggests that more than 50% of inventory records are not correct (Raman et al. (2001), Kang and Gershwin (2005)). DeHoratius and Raman (2008) identified several factors that influence record inaccuracy and emphasized the need to incorporate error characteristics into robust planning models. They pointed out that inventory record inaccuracy affects not only the operational performance of retailers but also the performance of upstream supply chain partners. Kök and Shang (2007) also considered inventory record inaccuracy issues in inventory management and provided an optimal joint inspection and replenishment policy when the inventory records were inaccurate. In this chapter, we study the impact of inaccurate information provided by the retailer on the supplier's cost. Suppose inaccurate demand information at the retailer caused by mis-scanning or theft is provided to the supplier via point-of-sales system and then the retailer corrects her inventory status and places an order for only as much as she needs while the supplier has already made his inventory decision based on false information. In this case, will information sharing still be beneficial to the supplier? If the loss due to errors is too big, it may be better for suppliers to ignore the demand information coming from retailers. Our main objective is to document conditions under which the supplier

should pursue such a strategy.

Despite its importance, only a few papers have explored the impact of inaccurate information on the benefit of information sharing. K  k and Shang (2009) and Camdereli and Swaminathan (2010) studied the impact of inaccurate inventory records on supply chains and regarded Radio-Frequency Identification (RFID) as a solution to eliminate the inaccuracy. On the other hand, we look into transaction errors from the information system such as RFID. Sari (2008) analyzed a four-echelon supply chain and concluded that inaccurate inventory information significantly influences the performance of collaboration initiatives and its impact under CPFR (collaborative planning, forecasting and replenishment) is bigger than that under VMI (vendor managed inventory). He observed that these practices are more sensitive to information errors when customer demand uncertainty is low and/or when lead times are short. Choi (2008) studied the impact of errors on the benefits of both upstream and downstream information sharing in supply chains with two stages. Our study is different from these studies in several aspects. First, we present a rigorous analytical model to capture information errors in supply chains, analyze the resulting optimization problems, and develop structural properties of the optimal solution. Further, we develop practicable guidelines for managing these systems.

Specifically, we address the following questions: (i) As the magnitude of errors in shared information increases, how does the supply chain behave? (ii) How do supply chain parameters affect the impact of errors on reducing the benefit of information sharing? and (iii) How much should the supply chain invest in reducing the magnitude of errors? Our analytical and computational results indicate that the benefit of

information sharing decreases as the magnitude of errors increases and the information is no more useful when the variability of errors exceeds the variability of end-customer demands. Demand variance, retailer order interval, and cost parameters affect the impact of information errors. The supply chain may make investments to reduce the magnitude of errors only when the cost reduction outweighs the investment, and this optimal investment is discussed.

The rest of this chapter is organized as follows. The supply chain setup is introduced in Section 2.2. Section 2.3 presents the analytical results focusing on how information errors affect the benefit of information sharing and how various parameters influence the impact of information errors. In Section 2.4, the computational results are shown to enhance understanding on the behavior of information errors. The simulation method also enabled extensions to vary demand distributions. Section 2.5 provides instructions on how much one should invest in reducing information errors through an analysis of optimal investments. Finally, Section 2.6 concludes by addressing the managerial implications of our results.

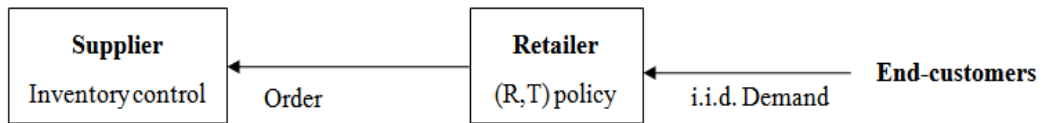
2.2. Supply chain setup

We consider a serial supply chain composed of a single supplier and a single retailer, as has been done by many researchers in the past work. We describe all the assumptions regarding the retailer's and the supplier's ordering processes with their policy structures along with the end-customer demands faced by the retailer.

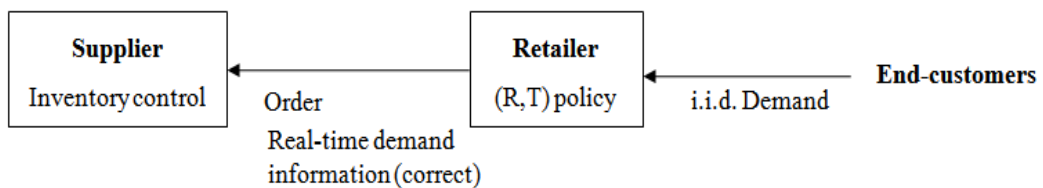
2.2.1. Models

Here we introduce three models for analyzing the impact of information errors on supply chain performance. When there is no information sharing, the retailer faces i.i.d. end-customer demands and places an order with the supplier according to an (R,T) inventory replenishment policy (Model NI). When there is information sharing (without errors), not only does the retailer place an order with the supplier but also she provides correct information about real-time end-customer demands to the supplier (Model IS). Finally, when there is information sharing with errors, the demand information provided by the retailer contains errors (Model IE). Figure 2.1 shows a brief description of the three models.

Model NI



Model IS



Model IE

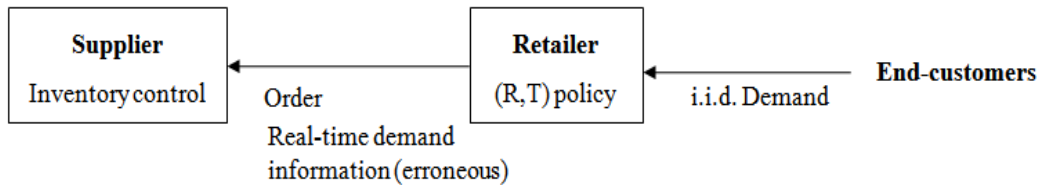


Figure 2.1: Models of information sharing with and without errors

While existing literatures focus on value of information sharing (which can be achieved by comparing Model NI and Model IS), our main objective is to examine the true value of information when there are errors by comparing Model NI and Model IE and scrutinize the impact of information errors by comparing Model IS and Model IE.

Note that we assume the retailer uses an (R,T) policy. The (R,T) inventory policy refers to the system under which the retailer places an order with the supplier every T^{th} period to bring her inventory level up to R . Optimal values of R and T are determined by minimizing the retailer's cost which includes a fixed cost that occurs whenever the retailer places an order. There are two main reasons why we analyze the case of the retailer using an (R,T) policy.

First, the (R,T) policy is often used in practice because it is relatively easy to implement. We usually observe that many retailers place an order and stock items on a regular basis such as on a specific day of the week or of the month, etc. Not only is the (R,T) policy widely used, but also it is more cost effective for the entire supply chain than a locally optimal (s,S) policy (Kwak and Gavirneni (2011)).

Second, compared to the case where the retailer places an order with the supplier every period, the benefit of information sharing to the supplier seems much clearer. When there is no information sharing, the supplier just observes the retailer order every T^{th} period. Thus, every T^{th} period, the supplier faces the cumulative uncertainty associated with T periods. When there is information sharing, the supplier has information on the realized demands for $(T-1)$ periods and faces demand uncertainty for only the T^{th} period. This is how the shared information contributes to

the supplier's cost savings by reducing demand uncertainties. For the scenario of information sharing with errors, we incorporate the error factors in the shared information (the information of the realized demands for $(T - 1)$ periods).

The sequence of events is as follows: (1) The supplier decides his production quantity and the production is completed immediately. If there is information sharing, the production decision is based on the information provided by the retailer. If there are errors in the shared information, the supplier's decision is based on false information though he recognizes the existence of errors. (2) The end-customer demand at the retailer is realized. The demand is fulfilled by the retailer's available inventory and excess demand is backlogged. If there is information sharing, the retailer gives the supplier information about real-time end-customer demands through a system such as ERP. (3) The retailer places an order with the supplier if it is the time to order (every T^{th} period) or does nothing otherwise. (4) The supplier ships the requested order quantity to the retailer. If the supplier does not have enough stock to satisfy this order, the shortfall is filled by a secondary source with ample supply, in which case the supplier incurs substantial penalty cost. Note that we adopt the "borrowed" assumption from Chen and Lee (2009) for analytical tractability. If backlog is not allowed for the supplier, exact analysis of his inventory problem is very hard. Chen and Lee (2009) discussed this simplifying assumption that the supplier can borrow the shortfall inventory from a secondary source and then return them after usage. (5) The goods shipped from the supplier arrive at the retailer.

At the end of each period, the retailer incurs unit holding cost (h_r) for excess

inventory and unit penalty cost (p_r) for backlogged demands while the supplier incurs unit holding cost (h_s) for excess inventory and unit penalty cost (p_s) for retailer demand that he cannot satisfy from on-hand inventory. Since information sharing benefits only the supplier (Gavirneni et al. (1999), Lee et al. (2000), etc.), we evaluate and compare the supplier's cost under different scenarios – no information sharing (Model NI), information sharing without errors (Model IS), and information sharing with errors (Model IE). The following notations are used for the supplier's costs of the three models throughout the paper.

C_{NI} = the supplier cost when there is no information sharing.

C_{IS} = the supplier cost when there is information sharing without errors.

C_{IE} = the supplier cost when there is information sharing with errors.

It is clear that C_{NI} is larger than C_{IS} and that C_{IE} is larger than C_{IS} . The key question we wish to study is when information sharing is no longer useful because of errors, i.e. when C_{IE} is larger than C_{NI} . In order to evaluate these supplier costs, we first analyze the retailer ordering decision for i.i.d. normal end-customer demand distributions, and then analyze the supplier production decision with the retailer order quantity as the demand faced by the supplier.

2.2.2. Ordering decisions

We assume the i.i.d. end-customer demand is normally distributed with mean μ and standard deviation σ . That is, the demand for a period is given by $D_t = \mu + \varepsilon_t$, where

$\varepsilon_t \sim \text{Normal}(0, \sigma^2)$. It is a reasonable assumption that both the retailer and the supplier have the information about the distribution of future end-customer demands since savvy retailers and suppliers will use historical data to determine the distribution of the demands (Raghunathan (2001)).

If u is defined as a mega-period for T periods, retailer's order quantity is expressed as

$$O_t = \begin{cases} Y_u & \text{if } t = uT \\ 0 & \text{otherwise} \end{cases}$$

$$\text{where } Y_u = \sum_{t=(u-1)T+1}^{uT} D_t = T\mu + \sum_{i=1}^T \varepsilon_{(u-1)T+i}.$$

Note that the retailer's order quantity can be negative because of the normality assumption of ε_t . As in Chen and Lee (2009), we allow for negative order quantity for ease of exposition and tractability. That is, the retailer can freely return excess inventory to the supplier. In addition, if the demand mean μ is large enough, the chance of a negative order quantity is negligible.

The supplier faces the retailer demand as Y_u in every mega-period u . Therefore, in order to determine the supplier's order up-to level S_u that minimizes the total expected holding and penalty costs in mega period u , the supplier needs to find the distribution of Y_u .

When there is no information sharing (Model NI), we assume that the supplier only knows the expected retailer order quantity and its variance. Then, the supplier would

deal with Y_u as having a normal distribution with mean $T\mu$ and variance $T\sigma^2$. The supplier's optimal order up-to level in this case is given by

$$S_u = T\mu + Z\sqrt{T}\sigma \text{ where } Z = \Phi^{-1}\left(\frac{p_s}{Th_s + p_s}\right).$$

With information sharing (Model IS), the supplier knows not only the expected retailer order quantity but also $\varepsilon_{(u-1)T+1}, \varepsilon_{(u-1)T+2}, \dots, \varepsilon_{(u-1)T+(T-1)}$ from the information of realized demands for $(T-1)$ periods $D_{(u-1)T+1}, D_{(u-1)T+2}, \dots, D_{(u-1)T+(T-1)}$. Thus, if there are no errors in the shared information, the supplier handles Y_u as having a normal distribution with mean $T\mu + \sum_{i=1}^{T-1} \varepsilon_{(u-1)T+i}$ and variance σ^2 . The supplier's optimal order up-to level in this case is given by

$$S_u = T\mu + \sum_{i=1}^{T-1} \varepsilon_{(u-1)T+i} + Z\sigma \text{ where } Z = \Phi^{-1}\left(\frac{p_s}{Th_s + p_s}\right).$$

Now, suppose that there are errors in the information provided by the retailer (Model IE). We assume that the information errors γ_t are i.i.d. normally distributed with mean 0 and standard deviation δ . The normality assumption of information errors allows for the possibility that the information transmitted is negative which may not be suitable for some settings. However, the possibility of negative demand information is very low when the mean demand is large enough as we assumed before. We proceed with the normality assumption because it enables us to obtain stronger analytical results. In the simulation study detailed in Section 2.4, we are able to accommodate, via truncation, that the information is non-negative and we are pleased to report that

all the analytical results are still well supported.

In this case, the supplier has to use the wrong information to decide his order-up-to level. However, since the supplier knows the demand distribution, it is highly possible that he realizes the existence of errors in the information. That is, a smart supplier will figure out the variability of information errors, δ^2 , given he assumes that the mean of errors is zero (Though DeHoratius and Raman (2008) demonstrated a bias in the errors of SKU-level data, the assumption of unbiased errors for our study is reasonable to pursue our objective to observe the impact of errors on benefit of information sharing since it is just a matter of parallel transference.), and optimize a part of his order-up-to level. Still, some loss due to errors is inevitable because the order-up-to level includes false information. Despite the supplier being aware that there exist errors in the information, he cannot just avoid information sharing because the erroneous information may still be more beneficial than no information.

In the case of information sharing with errors, instead of $\varepsilon_{(u-1)T+1}, \varepsilon_{(u-1)T+2}, \dots, \varepsilon_{(u-1)T+(T-1)}$, the supplier knows $\varepsilon'_{(u-1)T+1}, \varepsilon'_{(u-1)T+2}, \dots, \varepsilon'_{(u-1)T+(T-1)}$ where $\varepsilon'_{(u-1)T+1} = \varepsilon_{(u-1)T+1} + \gamma_{(u-1)T+1}, \dots, \varepsilon'_{(u-1)T+(T-1)} = \varepsilon_{(u-1)T+(T-1)} + \gamma_{(u-1)T+(T-1)}$. Thus, when there are errors in the information of the realized demands and the supplier knows the distribution of the errors, he treats Y_u as having a normal distribution with mean $T\mu + \sum_{i=1}^{T-1} \varepsilon'_{(u-1)T+i}$ and variance $\sigma^2 + (T-1)\delta^2$. The supplier's optimal order up-to level in this case is given by

$$S_u = T\mu + \sum_{i=1}^{T-1} \varepsilon'_{(u-1)T+i} + Z\sqrt{\sigma^2 + (T-1)\delta^2} \text{ where } Z = \Phi^{-1}\left(\frac{p_s}{Th_s + p_s}\right).$$

2.3. Cost comparisons

In this section, we determine the supplier's costs for the three models described above and evaluate their behavior. The supplier's long-run average cost is given by

$$\frac{1}{T} E[c(S_u - Y_u)]$$

$$\text{where } c(x) = Th_s \cdot \max(x, 0) + p_s \cdot \max(-x, 0).$$

The resulting costs of the three models are computed as follows:

$$C_{NI} = \frac{1}{T} (Th_s + p_s) \phi(Z) \sigma \sqrt{T},$$

$$C_{IS} = \frac{1}{T} (Th_s + p_s) \phi(Z) \sigma, \text{ and}$$

$$C_{IE} = \frac{1}{T} (Th_s + p_s) \phi(Z) \sqrt{\sigma^2 + (T-1)\delta^2}.$$

The cost savings out of information sharing is calculated as

$$C_{NI} - C_{IS} = \frac{1}{T} (Th_s + p_s) \phi(Z) (\sqrt{T} - 1) \sigma$$

if the information is totally error-free. However, if there are errors in the shared information (which is mostly probable), the actual cost savings will be

$$C_{NI} - C_{IE} = \frac{1}{T} (Th_s + p_s) \phi(Z) \left\{ \sigma \sqrt{T} - \sqrt{\sigma^2 + (T-1)\delta^2} \right\}$$

which generalizes the previous cost savings. This measure corresponds to the benefit

of information sharing gained by moving from the case of no information sharing to the case of information sharing with errors.

Theorem 2.1 *The supplier obtains no benefits from information sharing when the variability of information errors exceeds the variability of end-customer demands.*

Proof: Recall that the benefit of information sharing (savings in the supplier's cost) is

$$\text{calculated as } C_{NI} - C_{IE} = \frac{1}{T}(Th_s + p_s)\phi(Z)\left\{\sigma\sqrt{T} - \sqrt{\sigma^2 + (T-1)\delta^2}\right\}.$$

Information sharing will benefit the supplier when $C_{NI} - C_{IE} > 0$ and therefore, for information sharing to be beneficial, $(T-1)\sigma^2 > (T-1)\delta^2$, leading to $\sigma^2 > \delta^2$. ■

Theorem 2.1 provides a useful rule of thumb for supply chain managers on the threshold magnitude of errors that they can put up with. To make information sharing effective, the variance of information errors should be kept very much within the variance of end-customer demands. The following propositions further characterize the behavior of impact of information errors.

Proposition 2.1 *The benefit of information sharing (cost savings as a result of information sharing) is concave decreasing in the standard deviation of information errors.*

Proof: The benefit of information sharing (savings in the supplier's cost) is calculated

$$\text{as } C_{NI} - C_{IE} = \frac{1}{T}(Th_s + p_s)\phi(Z)\left\{\sigma\sqrt{T} - \sqrt{\sigma^2 + (T-1)\delta^2}\right\}.$$

In order to see the relationship between the cost savings and the error variability, let us define a term $K = \sigma\sqrt{T} - \sqrt{\sigma^2 + (T-1)\delta^2}$.

$$\frac{\partial K}{\partial \delta} = -\frac{(T-1)\delta}{\sqrt{\sigma^2 + (T-1)\delta^2}} \leq 0 \text{ for } \delta \geq 0.$$

$$\frac{\partial^2 K}{\partial \delta^2} = -\frac{(T-1)\sigma^2}{(\sigma^2 + (T-1)\delta^2)^{\frac{3}{2}}} < 0.$$

K is concave decreasing in δ for $\delta \geq 0$. ■

δ represents the magnitude of information errors. From proposition 2.1, when the magnitude of errors is large (small), the detrimental impact of a marginal increase is larger (smaller). Thus, the importance of analyzing information errors must be emphasized in practice because large magnitude of errors can cause a lot of damage to a supply chain.

In order to look at how the other parameters influence the impact of information errors, we compare the supplier's costs under information sharing with and without errors. The difference in the supplier's costs indicates the reduction in the benefit of information sharing due to information errors. Let S denote the impact of information errors and define a relative term $S = \frac{C_{IE} - C_{IS}}{C_{IS}} = \frac{\sqrt{\sigma^2 + (T-1)\delta^2} - \sigma}{\sigma}$ which stands for the relative cost increase due to errors in information sharing.

Proposition 2.2 *The detrimental impact of information errors (on reducing the benefit of information sharing) decreases as the standard deviation of end-customer demands increases.*

Proof: $\frac{\partial S}{\partial \sigma} = -\frac{(T-1)\delta^2}{\sigma^2 \sqrt{\sigma^2 + (T-1)\delta^2}} \leq 0$ ■

When the end-customer demands are less variable, the distorted demand due to information errors may be very different from the real demand compared to the case of more variable demands. Therefore, for industries with relatively less-variable demands, dealing with information errors should be one of the major issues. Besides, we can acquire further insights on how the retailer's order interval T affects the impact of information errors.

Proposition 2.3 *The detrimental impact of information errors (on reducing the benefit of information sharing to the supplier) increases with respect to the retailer's order interval T .*

Proof: Let $g(T) = \frac{\sqrt{\sigma^2 + (T-1)\delta^2} - \sigma}{\sigma}$ for an integer T .

$$g(T+1) - g(T) = \frac{\sqrt{\sigma^2 + T\delta^2} - \sqrt{\sigma^2 + (T-1)\delta^2}}{\sigma} \geq 0 \text{ for any integer } T > 0. \quad \blacksquare$$

The impact of information errors increases with T since more errors are included in the information when the retailer places orders less frequently.

2.4. Computational results

The simulation study is designed to confirm the analytical results for a larger set of demand distributions. We obtain the supplier costs of the three models (Model NI, Model IS, and Model IE) via simulation with an IPA (Infinitesimal Perturbation Analysis) procedure (Glasserman and Tayur (1995)) to compute optimal order up-to levels. It is assumed that the retailer uses an (R,T) inventory policy, and we found the

optimal (R,T) values for the retailer by comparing each average retailer cost under each optimal order-up-to level R given T (Rao (2003)). Six demand distributions are considered: Normal (20,3), Normal (20,5), Normal (20,7), Erlang (4,5), Erlang (2,10), and Exponential (20) (=Erlang (1,20)). The demands are always non-negative (truncated at 0 if needed). Since we assume i.i.d. demands, the demand variability is constant throughout the entire periods for each distribution. The following parameters are used for simulation: $(h_r=1, p_r=3, h_s=1)$ for all the experiments; $p_s = \{3, 6, 9, 12, 15\}$; $T = \{2, 3, 4, 5, 6\}$; $\delta = \{0.2\sigma, 0.4\sigma, 0.6\sigma, 0.8\sigma, \sigma, 1.2\sigma, 1.4\sigma, 1.6\sigma\}$ where δ is the standard deviation of information errors and σ is the standard deviation of the end-customer demand. Instead of the fixed cost, we vary the retailer's order interval. These parameters generate 1200 combinations and, for each combination, we compute the supplier costs of the three models (Model NI, Model IS, and Model IE).

Note that we get censored distributions of demand information by generating only nonnegative information. That is, during simulation, whenever demand information turns out to be negative, we discard it and generate another one. This way we can recognize the impact of normality assumption of errors. This restriction helps more on erlang distributions that have more chances to be negative than normal distributions. The interesting finding is that these simulation results almost fully support the analytical results obtained under the assumption of allowing negative information. That is, the possibility of negative information in the model does not significantly affect the impact of information errors on the supplier's cost.

Also, as a result of simulation, we observe that most properties analyzed in section 2.3 hold not only for i.i.d. normal demand distribution but also for i.i.d. erlang demand distributions.

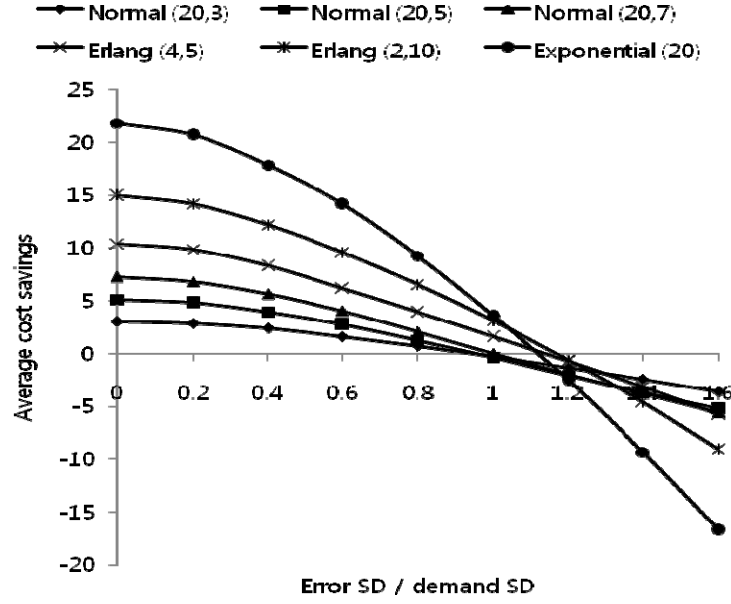


Figure 2.2: Benefit of information sharing with errors by various demand distributions

Figure 2.2 depicts the average cost savings from information sharing ($C_{NI} - C_{IE}$) under various demand distributions with respect to the magnitude of information errors as a ratio of standard deviation of errors to standard deviation of end-customer demands. The decrease of average cost savings with respect to the magnitude of information errors shows concavity as verified in proposition 2.1. That is, as the magnitude of information errors increases, information sharing becomes much less valuable and the marginal impact of errors increases. As theorem 2.1 says, there is no more benefit of information sharing when the variability of errors equals the variability of end-customer demands, and this critical point is also confirmed by

simulation results for i.i.d. normal demands. For i.i.d. erlang demands, the critical point is a little bit larger because we use the censored distribution of erroneous information. Dealing with only nonnegative demand information makes the error variability smaller than it is supposed to be. Still, it does not change the fact that the variance of information errors should be at least within the demand variance to make information sharing useful.

The following measure is defined to observe the relationships between the impact of information errors and the parameters varied in the simulation setting:

$$\text{Impact of information errors (\%)} = 100 \times \frac{C_{IE} - C_{IS}}{C_{IS}}.$$

This measure implies the relative cost increase caused by moving from information sharing without errors (Model IS) to information sharing with errors (Model IE).

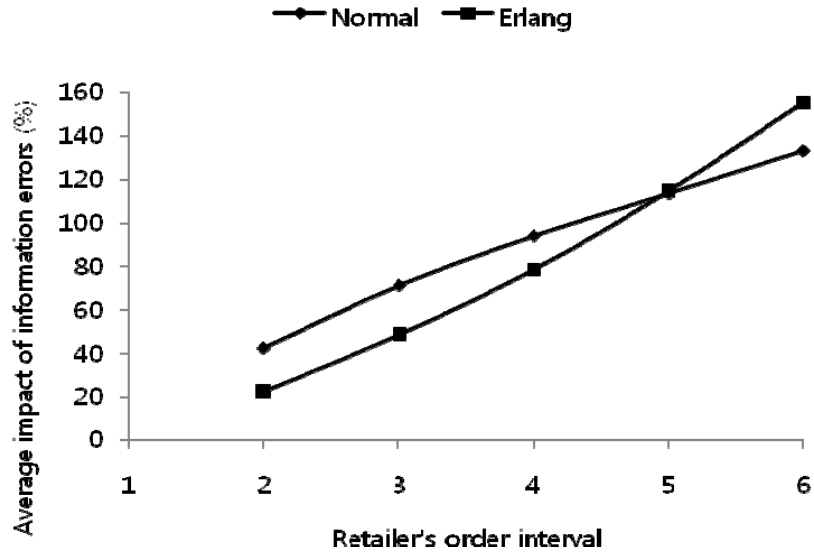


Figure 2.3: Impact of information errors with respect to retailer order interval

Figure 2.3 shows the average impact of information errors with respect to the retailer's order interval T . For all simulated distributions, information errors have greater effect when the retailer's order interval T is longer.

2.5. Investment to reduce information errors

If a supply chain can reduce the magnitude of information errors to benefit sufficiently from information sharing, to what extent should it invest in the effort? Suppose that the standard deviation of information errors δ becomes $\delta \exp(-\alpha I)$ when we invest I in an effort to reduce information errors; we want to know what the optimal investment level would be. Although we do not have empirical evidence to support the function for error reduction, this assumption captures the following desired property: the standard deviation of information errors remains the same as δ with no investment, while it approaches 0 if we invest a significantly large amount. A proper choice of α makes the assumption practically reasonable. To find the optimal investment I^* , the following problem needs to be solved.

$$\text{Maximize } C_{IE}(\delta) - C_{IE}(\delta \exp(-\alpha I)) - I$$

where $C_{IE}(\delta)$ = the supplier cost when the standard deviation of information errors is δ .

Proposition 2.4 *The optimal investment I^* is decreasing in α , increasing in the supplier's unit penalty cost p_s , increasing in standard deviation of information errors δ , decreasing in standard deviation of end-customer demands σ , and increasing in retailer's order interval T , respectively.*

Proof:

Recall that $C_{IE}(\delta) = \frac{1}{T}(Th_s + p_s)\phi(Z)\sqrt{\sigma^2 + (T-1)\delta^2}$.

$$C_{IE}(\delta) - C_{IE}(\delta \exp(-\alpha I)) - I = \frac{1}{T}(Th_s + p_s)\phi(Z)\left\{\sqrt{\sigma^2 + (T-1)\delta^2} - \sqrt{\sigma^2 + (T-1)(\delta \exp(-\alpha I))^2}\right\} - I.$$

This is concave in I , so the optimal investment which maximizes the cost savings is

$$I^* = \left(\frac{1}{2\alpha} \ln \frac{2(T-1)\left(\frac{Th_s + p_s}{T}\right)^2 \{\phi(Z)\}^2 \alpha^2 \delta^2}{1 + \sqrt{1 + 4\left(\frac{Th_s + p_s}{T}\right)^2 \{\phi(Z)\}^2 \alpha^2 \sigma^2}} \right)^+ . \quad \blacksquare$$

- i. As α increases, a relatively smaller investment is needed to reduce the same magnitude of information errors. α will be determined by the level of techniques to reduce information errors. If the technique is very efficient, even a small amount of investment can lead to a significant reduction in the standard deviation of information errors. For practical analysis, we can specify an adequate α by comparing an input (investment) and an output (reduction in the standard deviation of information errors) of a certain technology.
- ii. As the supplier's unit penalty cost increases, the term $(Th_s + p_s)\phi(Z)$ where $Z = \Phi^{-1}(p_s/(Th_s + p_s))$ increases as well (Chen and Lee (2009)). The optimal investment I^* is increasing in the term $(Th_s + p_s)\phi(Z)$ and thus increasing in the supplier's unit penalty cost p_s . Sharing precise information is especially important to the supplier if he incurs huge cost when he cannot meet the

retailer's request. Therefore, one might need to invest much more on reducing information errors in this case.

- iii. The efforts to reduce the magnitude of information errors will pay off more when the variability of errors is large in the first place. Therefore, the optimal investment is increasing in the variability of information errors, though the marginal increase is decreasing.
- iv. When the end-customer demands are more variable, sharing demand information will help the supplier a lot in cost savings and the negative impact of information errors will be relatively minor. Therefore, the optimal investment to diminish errors decreases as the demand variability increases.
- v. Finally, there is more need for error reduction when the retailer's order interval is longer. As analyzed before, the impact of information errors increases as the retailer's order interval T increases because errors accumulate for $(T-1)$ periods. Thus, we need to raise the investment to reduce information errors especially for longer order intervals.

Figures 2.4, 2.5, 2.6, and 2.7 show the computational results regarding optimal investment under the same simulation setting as in Section 2.4 only adding the variation of $\alpha = \{0.5, 1, 1.5, 2\}$. From these figures, proposition 2.4 is also validated for i.i.d. erlang demand distributions.

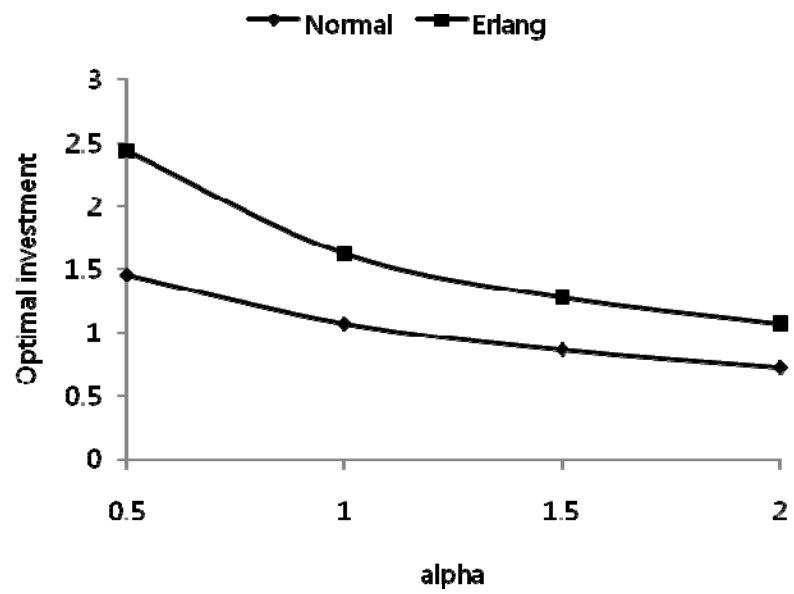


Figure 2.4: Optimal investment with respect to alpha

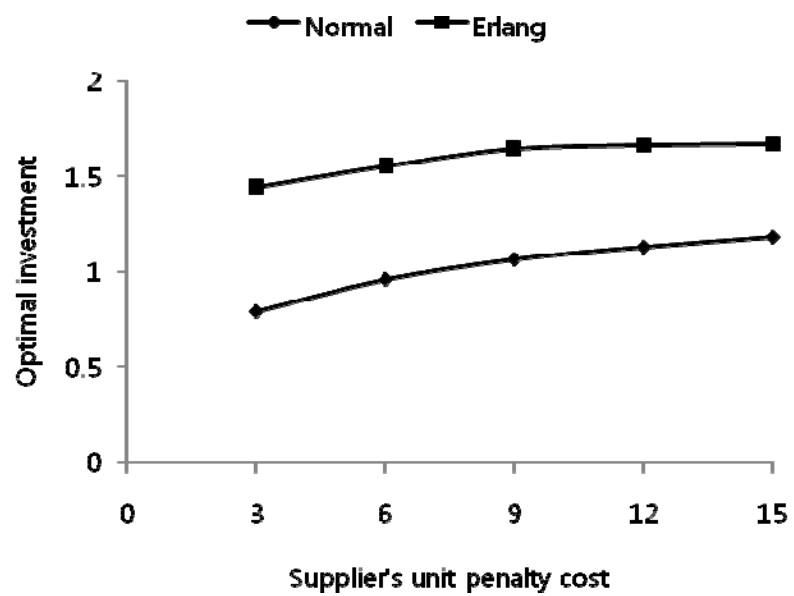


Figure 2.5: Optimal investment with respect to supplier unit penalty cost

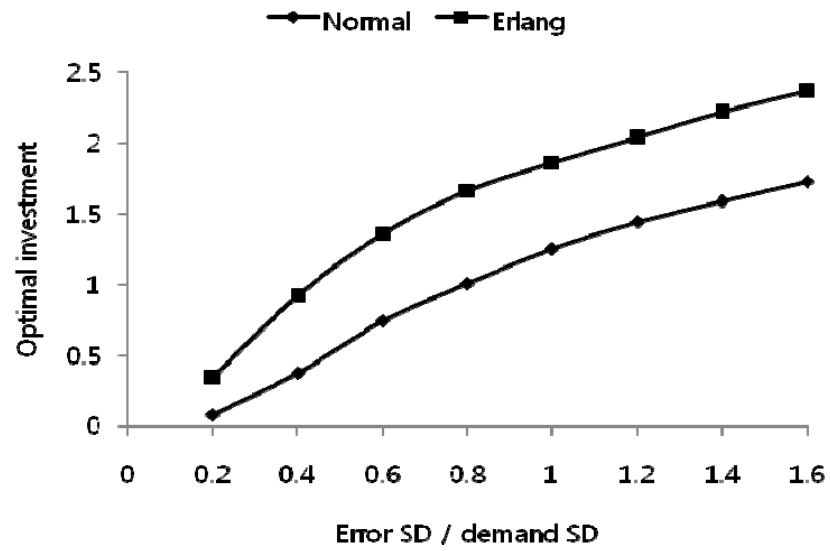


Figure 2.6: Optimal investment w.r.t. the ratio of error variability to demand variability

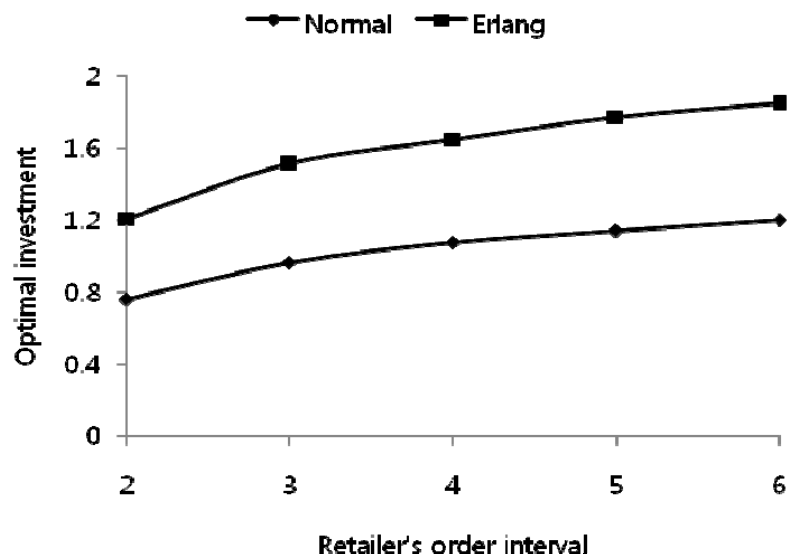


Figure 2.7: Optimal investment with respect to retailer order interval

2.6. Implications and conclusion

In this chapter, we have analyzed the impact of information errors on the benefit of information sharing. Though it is not surprising that existence of errors reduces the benefit of information sharing, it is not obvious how the supply chain costs are affected by information errors and what factors influence on the impact of errors. To our knowledge, this is the first study to rigorously quantify the behavior of supply chain performance regarding information sharing with errors. Given that information sharing is very costly, it is necessary to ensure that the benefit is greater than the cost. By comparing the supplier's costs with and without information errors, we have verified the following properties which have managerial implications.

First, as the variability of information errors increases, the benefit of information sharing decreases in a concave manner. This implies that more-variable information errors have bigger impacts on reducing the benefit of information sharing than less-variable information errors. Thus, we may accept small magnitude of errors in shared information, but large magnitude of errors will significantly harm supply chain performance. We observe that the information has no more value when the variability of information errors exceeds the variability of end-customer demands, making information sharing worse than not doing the practice. Information technology does not have to be perfect, but the errors due to the system should be at least within the variability of demands. This can be a critical point in judging whether the firm uses a certain information technology.

Moreover, the detrimental impact of information errors tends to increase as the

variability of end-customer demands decreases. Therefore, information sharing should be more carefully adopted for industries with relatively less-variable end-customer demands. As the retailer's order interval increases, the detrimental impact of information errors increases as well, because more errors are included in longer order intervals.

Finally, we have discussed how much one should invest in alleviating information errors. If the cost cutback achieved by reducing the magnitude of errors outweighs the investment amount, it is worthwhile to try. A crucial thought would be how to quantify error reduction by investment. The optimal investment amount is determined by cost parameters, error variability, demand variability, and retailer order intervals. It is increasing in the supplier's unit penalty cost, increasing in standard deviation of information errors, decreasing in standard deviation of end-customer demands, and increasing in retailer's order interval, respectively.

Efforts to improve supply chain performance such as information sharing do not always guarantee success, not because the purposes are insufficient but because uncontrollable errors may arise due to imperfect systems. Therefore, we should take into account the possibilities that the performance may not reach the expected goal. This study, by analyzing supply chain behavior with inaccurate information sharing, provides managerial implications for what circumstances are favorable to information sharing and what amount of investment is desirable to reduce information errors. Future research may extend this concept to investigate the impact of possible errors on other practices for supply chain improvement.

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CHAPTER 3

INVENTORY CONTROL WHEN SELLING TO HUMAN NEWSVENDORS

3.1. Introduction

We are living in a fast-changing business world where values of certain products diminish rapidly from the time they launch. The typical examples of such products include electronics that requires advanced technology and fashion apparels that can be only in style for a single selling season. The question about how much to prepare stock for these products with obsolescence is developed to a well-known newsvendor model in operations management research. The newsvendor model obtained its name from a newsvendor who has to decide how many newspapers should be ordered to maximize his profit, since too many orders end up with worthless leftovers and too few orders lead to foregone profits.

Newsvendor problems have been extensively studied with many extensions (Khouja (1999)). Most papers focus on the newsvendor problem only for retailers facing random demands rather than considering a supplier or a manufacturer who sells products to those retailers. This chapter studies inventory control for a supplier or a manufacturer when her customers deal with newsvendor problems. For example, suppose a manufacturer produces fashion apparel items and sells them to local retail stores that manage a newsvendor problem for every selling season. These retail stores must place an order with the manufacturer well in advance because the lead time from order placement to receipt of products is usually long for apparel industry (Fisher and

Raman (1996)). Considering that fashion products are time-sensitive, the manufacturer needs to prepare for stocks on hand to immediately meet the retailers' demands. Some apparel firms such as Nike place orders with original equipment manufacturers (OEMs) who must forecast the customer demand and produce the items before they receive orders.

Most newsvendor-type retailers in many industries including electronics, apparel, or food chain, etc. have suppliers. However, as mentioned earlier, there have not been many studies on the supply chain context. One of the reasons lies on an assumption of perfect rationality that retailers will always order an optimal quantity that is a well-known newsvendor solution, in which case there is no uncertainty in the supplier's stock decision.

However, recent experimental research in the newsvendor setting revealed that retailers do not make optimal inventory decisions. Experiments conducted by Schweitzer and Cachon (2000) covering thirty periods reported that there is a significant tendency of anchoring on the mean demand and that subjects choose a stocking level that is between the mean demand and the optimal quantity. They also found weak support for a chasing demand pattern. As follow-up papers, Bolton and Katok (2008) and Bostian et al. (2008) confirmed the experimental results of Schweitzer and Cachon (2000) and further studied the effect of learning. Benzion et al. (2008) showed that normal demand distribution generates the similar results to those under uniform demand distribution and that the order quantity is affected by previous-round results. While these non-optimal behavioral patterns are acknowledged to be

robust, there has been no research that studies their impact on supply chain performance.

When retailers make non-optimal inventory decisions for a newsvendor situation, what should be the inventory control strategy of a supplier who sells the products to the retailers? Will understanding retailers' behaviors help the supplier manage inventories? This study investigates whether a supplier could improve her inventory decision by incorporating the retailers' behaviors in the decision making processes.

We (i) develop mathematical models for the newsvendor decision maker; (ii) estimate the parameters using data from experiments with human subjects; (iii) determine the demand distribution the supplier faces; and ultimately (iv) observe the cost savings that the supplier achieves by incorporating these behavioral tendencies into her decision making.

Using the data from our own experiments, we estimate the possible reduction in supplier costs and determine the factors that significantly affect it. From the data showing an obvious demand-chasing pattern, we observe that a supplier can save considerable inventory costs by taking into account those retailers' behavioral tendencies. The amount of cost savings depends on the characteristics of the data, and it should be studied how we can determine the types of retailers' behaviors. We propose a model assuming that retailers are mean-anchoring with probability p , demand-chasing with probability r , and random with probability $(1 - p - r)$. Values of these probabilities might work as a clue to decide the retailers' behavioral

tendencies. If p or r is large enough, this model can be used by a supplier to estimate the distribution of the demand she faces.

We also propose a useful methodology for the supplier to estimate the demand distribution: Bayesian regression is an appropriate way of estimating model parameters when the sample size is small. A supplier can estimate the distribution of each retailer's order quantities and compute the potential inventory cost by Bayesian regression analysis.

In addition, by analyzing experimental results, we discovered that considering individual behaviors helps the supplier estimate the demand distribution better than considering aggregate random behaviors of retailers, which is expected intuitively as well. From the additional experiments, we obtained an insight about the effect of end-customer demands' variance: when the demand variance is larger, the supplier gets more benefit from the information about retailers' behaviors. Besides, we believe there are many more interesting and valuable research ideas regarding this subject.

The remainder of this chapter is as follows. In Section 3.2, we review some relevant literatures and point out the contribution of this study. Section 3.3 describes a supply-chain setup and five models used in this research. In Section 3.4, we analyze the possible cost savings from understanding retailers' behaviors with our own experimental data. Section 3.5 discusses several issues regarding the findings of this research. Section 3.6 concludes the chapter and suggests future research directions.

3.2. Literature review

Behavioral operations management is a relatively new research field with significant potentials. Recently, researchers are paying increasing attentions to behavioral studies in operations management area, not only because they realize human factors should be considered to explain real-world phenomena but also because behavioral experimentation and mathematical modeling complement each other (Bendoly et al. (2006)).

A group of behavioral papers are summarized in several review papers such as Boudreau et al. (2003), Loch and Wu (2005), and Bendoly et al. (2006). Further, Gino and Pisano (2008) guide some future research directions, and Bendoly et al. (2010) review related knowledge for research in behavioral operations. Particularly for supply chain management, some literatures emphasize the importance of behavioral research (Tokar (2010), Bachrach and Bendoly (2011), Knemeyer and Naylor (2011), Siemsen (2011)). Yet, there are relatively fewer papers about behavioral operations of supply chains, which are limited to only couple of issues such as bullwhip effect (Croson and Donohue (2006)) and contracting (Katok et al. (2008), Katok and Wu (2009), Kalkanci et al. (2011)). There are very few papers that incorporate human behavioral effects into supply chain operational performance. Kalkanci et al. (2011) observes via human experiments that the simple price-only contract is more efficient and more profitable to a supply chain than the theoretically superior quantity-discount contract. However, especially in newsvendor arena, this study is the only one that investigates the effect of behavioral tendencies on supply chain performance.

For the topic of newsvendor problems, some researchers have discussed important issues about behavioral operations, though not in a supply chain context. Schweitzer and Cachon (2000) discover that human newsvendors do not make optimal inventory decisions and explain the behaviors by anchoring and insufficient adjustment heuristics. Gavirneni and Isen (2010) study behavioral aspects of newsvendor inventory decisions through verbal protocol analysis. Benzion et al. (2010) observe that human subjects do not make superior optimal newsvendor inventory decisions when they know demand distribution, compared to when they do not. We refer to Schweitzer and Cachon (2000) to use their heuristics as a way of explaining retailers' behavioral tendencies, but still the focus of our study is on an entire supply chain: how the behavioral tendencies affect supply chain performance.

The methodology used in this study is also relatively novel in operations management area, not to mention it is the most suitable way to analyze the experimental data. Azoury and Miyaoka (2009) state that a Bayesian approach to demand modeling is especially appropriate in an environment of high uncertainty with little historical data. By using Bayesian regression method when analyzing the experimental data, we were able to estimate the model parameters to determine the distribution of retailers' order quantities so that a supplier can predict her inventory cost. Interested readers may refer to Gelman et al. (2004) and Congdon (2007) for more details about Bayesian regression analysis.

To sum up, the academic contribution of this study can be pointed out as follows. First, this is the first that studies the effect of retailers' irrational inventory decisions on supply chain performance. Second, this also contributes to the newsvendor

literatures by considering behavioral aspects of newsvendor decisions in a supply chain context. Third, this study uses Bayesian regression analysis which is an effective methodology to compute the possible cost savings as well as to propose a way to determine the individual decision-maker's behaviors or forecast demand distribution based on order history.

3.3. Models

3.3.1. Setup

We consider a supplier selling a single product to N independent retailers at a unit wholesale price of W per unit. She procures the product of C per unit and if she can sell it to a retailer, makes a margin of $W - C$. On the other hand, if the unit is left over due to a low demand from the retailers, she foregoes the C dollars spent in acquiring it. Each retailer, in turn, faces random (uniformly distributed between 0 and U) demands from end-customers and must make a newsvendor decision about how much inventory to acquire. The retailers acquire the product at W per unit and sell it to the end-customers at P per unit. Unsatisfied demands at the retailers are assumed to be lost. Unsatisfied demand at the supplier is satisfied via expediting which costs the supplier C_e per unit. The retailers will always receive their whole order and thus in effect face uncapacitated replenishment. Any excess inventories at the retailers and the supplier are salvaged at no additional revenue at the end of the period. The sequence of events in each period is as follows:

1. The supplier decides her stocking level. The production capacity is infinite.

2. The retailers place their orders with the supplier and receive them from the supplier in full. If the supplier does not have enough inventory to meet all of the retailers' demands, she will use an expediting process to immediately acquire additional inventory and ships them to the retailer.
3. The retailers observe the end-customer demands and satisfy as much as possible from on-hand inventory. Unsatisfied end-customer demands at the retailers are lost.
4. Excess inventories at the supplier and the retailers are salvaged at no additional revenue.

The system is a repeated newsvendor problem with the retailers and the supplier making decisions that maximize their own expected profits.

3.3.2. Retailer and supplier behavior

The retailer's stocking level decision is one of a newsvendor with infinite capacity and thus the optimal solution is well known. The information needed to solve for a newsvendor problem consists of an overage cost (C_o) associated with every unit of unsold inventory, an underage cost (C_u) associated with every unit of demand lost due to lack of inventory, and demand distribution ($F(\cdot)$). Given this information, the optimal purchasing quantity can be computed as $F^{-1}\left(\frac{C_u}{C_o+C_u}\right)$. Under our setup, the underage cost is $P - W$ and the overage cost is W for retailers.

Let us first consider that all retailers behave optimally. The optimal order quantity is $\frac{P-W}{P} \times U$ and since the problem renews in every period, the order quantity would be

the same in all periods. The total demand seen by the supplier in each period is $\frac{P-W}{P} \times NU$. Since there is no randomness in the demand seen by the supplier, her stocking level decision is trivial and her optimal profit is $(W - C) \times \frac{P-W}{P} \times NU$. There is no additional cost related to inventory decision of the supplier.

On the other hand, if retailers behave non-optimally, they do not make optimal decisions and demonstrate significant variability in their order quantities. This variability necessitates the supplier to make an appropriate newsvendor decision. The total demand seen by the supplier is equivalent to the sum of all retailers' order quantities. It is reasonable to assume that each retailer's order quantity is normally distributed because normal distribution is most commonly used for stochastic variables. Su (2008) found that the boundedly rational newsvendor's order quantity follows a truncated normal distribution for uniformly distributed end-customer demands.

The supplier's stock decision is affected by how she determines the distribution of the retailers' order quantities. We develop five models based on different assumptions on retailers' behaviors. For each model, we define the retailer decision making process at an individual level and characterize the resulting demand faced by the supplier. Human retailers will behave all differently, so it is natural to model the retailers' behaviors at an individual level rather than in aggregate. Following notations are used through all models:

Q_{it} : order quantity placed by retailer i at time t

Q^* : optimal order quantity for retailers (optimal newsvendor solution)

d_t : observed end-customer demand at time t

Model R: The supplier assumes that all retailers' order quantities are random.

Each retailer's order quantity can be modeled as:

$$Q_{it}^R = \beta^R Q^* + \varepsilon_{it}^R$$

where ε_{it}^R is the error term with distribution $Normal(0, (\sigma_i^R)^2)$. Then, the demand

seen by the supplier is $Normal\left(N\beta^R Q^*, \sum_{i=1}^N (\sigma_i^R)^2\right)$.

Model IR: The supplier assumes that each retailer's order quantity follows normal distribution with individual mean and variance.

Each retailer's order quantity can be modeled as:

$$Q_{it}^{IR} = \beta_i^{IR} Q^* + \varepsilon_{it}^{IR}$$

where ε_{it}^{IR} is the error term with distribution $Normal(0, (\sigma_i^{IR})^2)$. Then, the demand

seen by the supplier is $Normal\left(\sum_{i=1}^N \beta_i^{IR} Q^*, \sum_{i=1}^N (\sigma_i^{IR})^2\right)$.

Model M: The supplier assumes that the retailers have mean-anchoring tendencies.

Retailers anchor on the mean demand ($\frac{U}{2}$) and insufficiently adjust towards the optimal order quantity (Q^*). This is one of the heuristics suggested by Schweitzer and

Cachon (2000), and it explains well the pattern of order quantities between mean demand and optimal order quantity. We model this mean-anchoring behavior as follows:

$$Q_{it}^M = a_i^M \frac{U}{2} + (1 - a_i^M) Q^* + \varepsilon_{it}^M$$

where a_i^M is an individual-specific parameter representing the magnitude of the mean-anchoring tendencies, and ε_{it}^M is the error term with distribution $Normal(0, (\sigma_i^M)^2)$. In this case, the demand seen by the supplier is $Normal\left(\sum_{i=1}^N \left\{ a_i^M \frac{U}{2} + (1 - a_i^M) Q^* \right\}, \sum_{i=1}^N (\sigma_i^M)^2\right)$.

Model D: The supplier assumes that the retailers have a tendency to chase the previous demand.

Retailers anchor on a prior order quantity ($Q_{i,t-1}$) and adjust towards prior demand (d_{t-1}). This is another heuristic suggested by Schwetizer and Cachon (2000). We model this demand-chasing behavior as follows:

$$Q_{it}^D = b_i^D d_{t-1} + (1 - b_i^D) Q_{i,t-1}^D + \varepsilon_{it}^D$$

where b_i^D is an individual-specific parameter representing the magnitude of the demand-chasing tendencies, and ε_{it}^D is the error term with distribution $Normal(0, (\sigma_i^D)^2)$. In this case, the demand seen by the supplier is

$$Normal\left(\sum_{i=1}^N \left\{ b_i^D d_{t-1} + (1 - b_i^D) Q_{i,t-1}^D \right\}, \sum_{i=1}^N (\sigma_i^D)^2\right).$$

Model B: The supplier assumes that the retailers are both mean-anchoring and demand-chasing.

If each retailer has a mean-anchoring tendency with individual probability p_i and a demand-chasing tendency with individual probability r_i , we can model this behavior as follows:

$$Q_{it}^B = p_i^B \left\{ a_i^B \frac{U}{2} + (1 - a_i^B) Q^* \right\} + r_i^B \left\{ b_i^B d_{t-1} + (1 - b_i^B) Q_{i,t-1} \right\} + (1 - p_i^B - r_i^B) Q^* + \varepsilon_{it}^B.$$

where ε_{it}^B is the error term with distribution $Normal(0, (\sigma_i^B)^2)$. Then, the demand seen by the supplier is

$$Normal\left(\sum_{i=1}^N \left[p_i^B \left\{ a_i^B \frac{U}{2} + (1 - a_i^B) Q^* \right\} + r_i^B \left\{ b_i^B d_{t-1} + (1 - b_i^B) Q_{i,t-1} \right\} + (1 - p_i^B - r_i^B) Q^* \right], \sum_{i=1}^N (\sigma_i^B)^2\right).$$

Let S denote the supplier's stock level and D denote the demand faced by the supplier, i.e., sum of all the retailers' order quantities. Suppose this demand is normally distributed with mean μ and standard deviation σ . When the supplier's stock level (S) is greater than or equal to the retailers' demands (D), the supplier's profit would be

$$\pi(S) = (W - C)D - C(S - D).$$

When the suppliers' stock level (S) is less than the retailers' demands (D), the supplier's profit would be

$$\pi(S) = (W - C)D - C_e(D - S).$$

Therefore, the supplier cost associated with inventory decision can be expressed as

$$C(S) = E[C(S - D)^+ + C_e(D - S)^+]$$

The optimal stock level S^* that minimizes this inventory cost is a well-known newsvendor solution,

$$\begin{aligned} S^* &= F^{-1}\left(\frac{C_e}{C+C_e}\right) \\ &= \mu + \sigma\Phi^{-1}\left(\frac{C_e}{C+C_e}\right) \end{aligned}$$

where $\Phi(\cdot)$ is the standard normal distribution.

The resulting supplier cost is

$$C(S^*) = \sigma(C + C_e)\phi\left(\Phi^{-1}\left(\frac{C_e}{C+C_e}\right)\right)$$

where $\phi(\cdot)$ is the pdf of standard normal distribution.

Note that the supplier is smart enough to solve the repeated newsvendor problem, that is, we assume perfect rationality for the supplier. Thus, if the supplier is able to properly estimate the demand distribution, she can compute the supplier's inventory cost as it is determined by the standard deviation of her demand.

3.4. Analysis

The key question for the supplier to solve her repeated newsvendor problem is how to estimate the distribution of retailers' order quantities given the retailers' order history. As a way to obtain the retailers' order history for our analysis, we conducted newsvendor experiments using human subjects. With the experimental data, we estimate the distribution of retailers' order quantities by models under different

assumptions on retailers' behaviors, and observe how much a supplier can improve the decision making process by incorporating information about retailers' behaviors.

The two experiments reveal that a supplier can significantly reduce her inventory cost by considering retailers' behavioral tendencies. The second experiment not only validates the point but also examines the effect of end-customer demand variances.

3.4.1. Experiment 1

Experiment 1 was done by recruiting 68 undergraduate students at Georgia State University. The participants were requested to make the inventory decisions for extra credits. They were able to obtain 3 points for a required course only when they finished all the 50 rounds. Since the three-point credit could change the grade (e.g. from grade B to grade A), it is a strong incentive to students. Each subject was assigned a computer and asked to decide the order quantity for each round. Information about the retail price, the purchasing price, and the demand distribution was shown on the screen. Except for the first round, the subjects were informed of the actual demand of the previous round and the resulting profit/loss they made in each round. The retail price is \$1000, the purchasing price is \$300, and demand is discrete and uniformly distributed between 1 and 20000. Because of its simplicity, uniform distribution is frequently used in the newsvendor experiments (Schwartz and Cachon (2000), Bolton and Katok (2008), Bostian et al. (2008), Gavirneni and Xia (2009)). The results under normal demand distribution are usually not so different (Benzion et al. (2008)). The newsvendor solution (optimal order quantity) of our experiment is 14000. However, similarly as shown in several experiments from other articles, the

subjects did not order 14000 units most of the time. We used only 60 subjects' answers for analysis after excluding unreliable data. Figure 3.1 depicts the average order quantity across subjects along with the actual demand for each round.

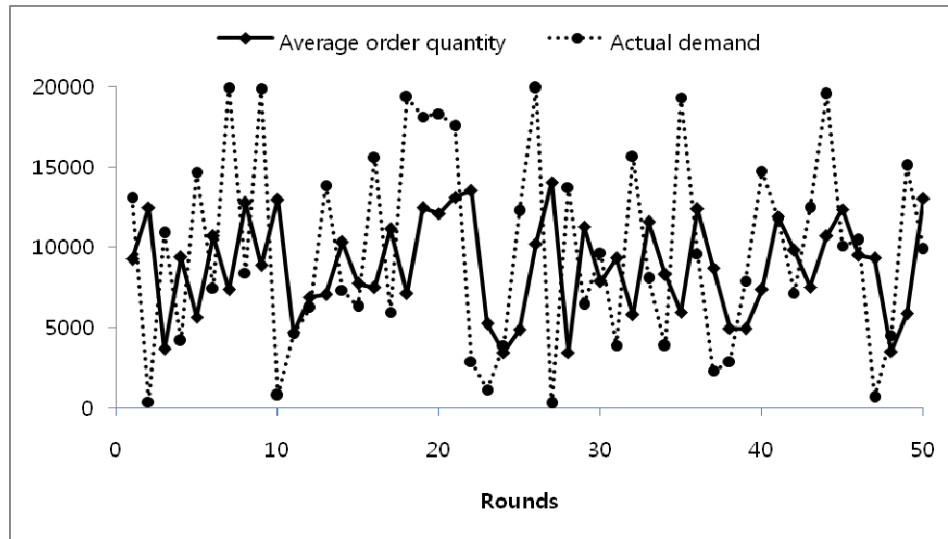


Figure 3.1: Experimental data – Experiment 1

Unlike other literatures, there is no “pull-to-center” effect in our data from Experiment 1, that is, the average order quantities do not always lie between mean demand (10000) and optimal order quantity (14000), only in 19 rounds out of 50 rounds (38%). Of all the decisions (3000 decisions), 31.23% of order quantities are between mean demand and optimal order quantity. However, clearly, we can see a very strong pattern of chasing demands. Of all the decisions excluding the first round (2940 decisions), 75.24% changed the order quantities across rounds in the direction of previous demand, 10.99% changed the order quantity away from previous demand, and 13.77% didn't change the order quantity.

We carried out a Bayesian regression analysis to estimate the model parameters described in section 3.2. Bayesian regression is widely used especially in marketing research due to its powerful ability to analyze experimental data even when the sample size is relatively small. As we observe individual retailers' ordering behaviors, Bayesian regression would provide the best estimation for model parameters. Publicly available Windows-based software WinBUGS (Windows Bayesian inference Using Gibbs Sampling) is used for Bayesian regression on our data. WinBUGS is developed for the Bayesian analysis of complex statistical models using Markov chain Monte Carlo methods. The results of Bayesian regression estimation are summarized in Table 3.1.

Table 3.1: Parameter estimation - Experiment 1

	SD of demand	Average values					
		β	a	b	p	r	σ
Model R	39062.91	0.629					5043.00
Model IR	38127.00	0.628					4784.05
Model M	41109.61		0.890				5177.60
Model D	30117.76			0.601			3647.46
Model B	28927.66		0.703	0.676	0.241	0.691	3516.63

We provide average values of each parameter, but all the individual-specific parameters are available upon request. Also, we can provide the distribution of each individual-specific parameters, as Bayesian regression estimates parameters with probabilities unlike other regression methods.

Remember that the supplier's inventory cost is determined by the standard deviation of the demand the supplier sees. Therefore, we need to compare the standard deviation of the suppliers' demand by models, which is computed as follows.

$$\sigma = \sqrt{\sum_{i=1}^N (\sigma_i^m)^2}$$

where m indicates Model R, IR, M, D, and B, respectively, as far as each model estimates the demand distribution properly.

We define a performance measure for cost comparisons as:

Improvement of Model m (%) = $100 \times (\text{Estimated cost of Model R} - \text{Estimated cost of Model } m) / \text{Estimated cost of Model R}$

This measure implies how much the supplier's inventory cost is saved by estimating demand distribution with Model m , compared to assuming that retailers' orders are random in aggregate. Table 3.2 shows the Improvement of each model.

Table 3.2: Improvement - Experiment 1

	Improvement (%)
Model IR	2.396
Model M	-5.239
Model D	22.899
Model B	25.946

The highest Improvement, about 26%, is obtained when each retailer is assumed to be both mean-anchoring and demand-chasing with individual probabilities. The cost reduction when all retailers are assumed to be demand-chasing is considerable as well at 22.90%. However, assuming all retailers are mean-anchoring turns out to rather increase the supplier's inventory cost.

The plausible explanation is that our data from Experiment 1 presents obvious demand-chasing behaviors, but not clear mean-anchoring behaviors. In other words, if

a model explains the data (order history) well, a supplier can save significant inventory cost by estimating her demand with the model; but otherwise, it leads to a worse outcome.

The fit of models to the data can be evaluated by a measure, DIC (Deviance Information Criterion), provided in Table 3.3 for our data.

Table 3.3: DIC - Experiment 1

	DIC
Model R	59669.4
Model IR	59147.0
Model M	59680.8
Model D	56083.3
Model B	55894.8

The DIC is defined in analogy with the AIC (Akaike's Information Criterion). So, models with smaller DIC provide a better fit. It gives a measure for how well each model fits the data and penalizes for the number of parameters, similar to the AIC. Therefore, among the five models we developed, Model B provides the best fit for the data as well as generates the lowest inventory cost.

The important finding from the analysis is that a supplier can obtain significant cost savings if she incorporates the information about retailers' ordering behaviors (e.g. mean-anchoring, demand-chasing, or both) into the decision making processes. It is notable that inappropriate assumption on retailers' behaviors is of no use or leads to even worse performance.

3.4.2. Experiment 2

Another experiment may enable more rigorous analysis as well as check whether our point applies to other data. 65 undergraduate students at Georgia State University were recruited for this experiment. They were requested to make simultaneous inventory decisions for two products for 50 periods given the information about end-customer demands and cost parameters.

This time we consider two products with different demand distributions, in order to observe the effect of demand variances. For product #1, the demand is discrete and uniformly distributed from 1 to 20000, and for product #2, the demand is discrete and uniformly distributed from 1 to 500. For both products, the selling price is \$10 and the purchasing price is \$3. These are also repeated newsvendor problems for each retailer. The optimal order quantity should be 14000 for product #1, and 350 for product #2. We had to select only 23 subjects' responses that are suitable for analysis for both products.

The experimental results are shown in Figure 3.2 and Figure 3.3 by plotting the average order quantities across subjects in each period.

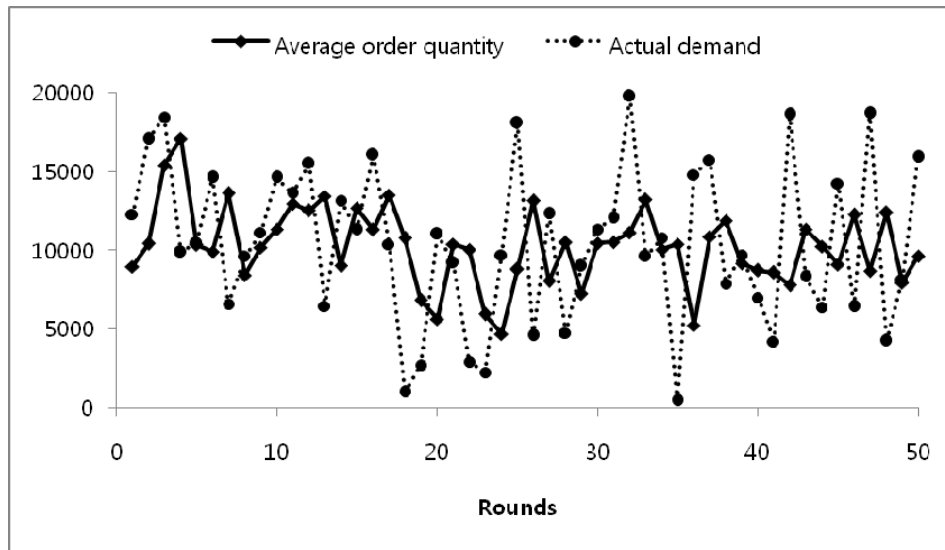


Figure 3.2: Experimental data - Experiment 2, product #1

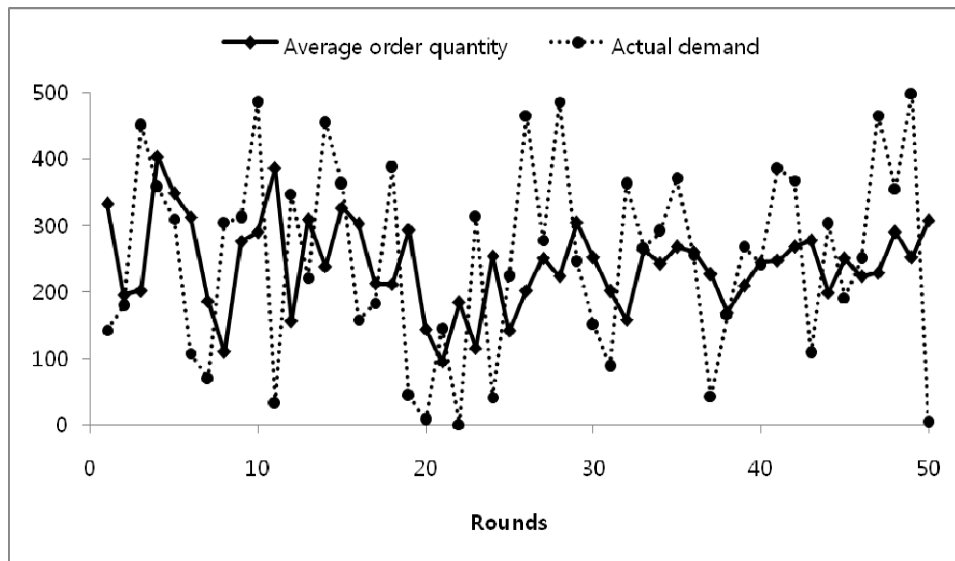


Figure 3.3: Experimental data - Experiment 2, product #2

Similarly to Experiment 1, the order quantities vary, and show a demand chasing pattern, though not as strong as that of Experiment 1. For product #1, of 1127

decisions excluding first-round decisions, 65.48% changed the order quantities in the direction of the previous demands, 9.58% changed the order quantities away from the previous demands, and 24.93% didn't change the order amounts. For product #2, of 1127 decisions, 62.64% changed the order quantities in the direction of the previous demands, 9.49% changed the order quantities away from the previous demands, and 27.86% didn't change the order amounts. Of all the 1150 decisions, 47.22% of order quantities lie between the mean demand (10000) and the optimal order quantity (14000) for product #1, and 36.61% of order quantities lie between the mean demand (250) and the optimal order quantity (350) for product #2, providing some evidence to a little bit more mean-anchoring tendency than Experiment 1.

Again, we estimate the parameters of five models with the data by Bayesian regression, and the results are summarized in Table 3.4 and Table 3.5.

Table 3.4: Parameter estimation and DIC - Experiment 2, product #1

Product #1	SD of demand	Average values						DIC
		β	a	b	p	r	σ	
Model R	22852.14	0.735					4765.00	22744.0
Model IR	19837.87	0.735					3943.83	22029.0
Model M	22296.74		0.724				4290.09	22331.4
Model D	13556.61			0.519			2507.67	19380.6
Model B	12880.20		0.602	0.598	0.200	0.691	2352.72	19233.9

Table 3.5: Parameter estimation and DIC - Experiment 2, product #2

Product #2	SD of demand	Average values						DIC
		β	a	b	p	r	σ	
Model R	579.82	0.690					120.90	14292.7
Model IR	512.48	0.690					102.82	13643.3
Model M	564.63		0.831				113.09	14037.6
Model D	397.69			0.502			74.36	12417.5
Model B	386.15		0.689	0.545	0.225	0.707	72.02	12340.7

Table 3.6 and Table 3.7 provide the information about the cost improvement that can be achieved from estimating demand distribution with each model instead of assuming aggregate randomness. For both products, the estimated supplier cost is the lowest when the supplier assumes that retailers are both mean-anchoring and demand-chasing with their own probabilities (Model B). The supplier can save the cost by about 44% for product #1 and about 33% for product #2 compared to when she assumes random distribution for retailer orders in aggregate (Model R).

Table 3.6: Improvement - Experiment 2, product #1

	Improvement (%)
Model IR	13.190
Model M	2.430
Model D	40.677
Model B	43.637

Table 3.7: Improvement - Experiment 2, product #2

	Improvement (%)
Model IR	11.613
Model M	2.619
Model D	31.412
Model B	33.402

From the two experiments, we observe that a supplier can improve her inventory decision significantly by assuming that retailers have anchoring tendencies.

3.5. Discussion

In this section, we go over several issues worth to discuss from the experimental results.

First, the decision making processes can be improved significantly by considering individual behaviors. In all cases, Model IR (assuming individual randomness) is superior to Model R (assuming aggregate randomness), implying that more precise forecasting is possible by understanding individual behaviors instead of aggregate behaviors. Particularly, the supplier benefits most from assuming that retailers are both mean-anchoring and demand-chasing with their individual probabilities (Model B). For our data, the supplier can save the inventory cost by as much as about 26% at least. The magnitude of cost savings depends on the data, but it is certain that the information about retailers' behavioral tendencies helps the supplier's inventory decision. Model B provides the best fit to all data in terms of DIC, that is, considering both mean-anchoring and demand-chasing behavioral tendencies explains the given order history well.

Second, we need to precisely identify the retailers' behavioral tendencies. Our experimental results show that assuming only mean-anchoring retailers may lead to even worse performance for the supplier than assuming just random orders, when the data does not tell a clear sign of mean-anchoring tendencies. On the other hand, assuming only demand-chasing retailers improves the suppliers' inventory decision quite considerably, as the data shows a strong demand-chasing pattern. Therefore, we might say the retailers in our data are demand-chasing. It is not surprising that Model

B generates the best outcome, as Model M and Model D are its trivial cases. Still, it is important to identify the retailer's behavioral tendencies because it will affect the usefulness of this approach.

We need to think of how we can determine whether the retailers are mean-anchoring, demand-chasing, or neither. For the mean-anchoring tendency, we may observe whether the average order quantities are usually between the mean demand and the optimal order quantity. In our data, out of 50 rounds, 19 average order quantities (38%) lie between the mean demand and the optimal order quantity for Experiment 1, 28 (56%) for product #1 in Experiment 2, and 21 (42%) for product #2 in Experiment 2. For the demand-chasing tendency, we may count how many times the average order quantity changes towards the previous demand instead of away from it. In our data, for 49 rounds excluding the first round, most average order quantities change toward the previous demand: 45 (91.8%) for Experiment 1, 46 (93.9%) for product #1 in Experiment 2, 41 (83.7%) for product #2 in Experiment 2. Another possible method to determine retailer's behaviors might be using the probability parameters of Model B. In all experiments, the sum of average parameters p and r is around 0.9, and that may be the reason why Model B improves the supplier's inventory decision so significantly. If retailers' behaviors are ambiguous in both mean-anchoring and demand-chasing, the sum of average probability parameters p and r might be relatively low and Model B might not improve the decision that much. In such case, we can still use the Model B as a tool to identify the retailer's behaviors.

Third, Experiment 2 was designed to observe the effect of demand variance as well as to check validity of the result of Experiment 1. To examine whether individual retailers have a consistent behavioral tendency on ordering two different products, we compared individual-specific model parameters through two-sample t test. As a result, we cannot find an evidence pointing that the set of model parameters are not different across two products with different demand variances. Although, it seems that the information about retailers' behavioral tendencies is more useful when the end-customer demands are more variable. It is probably because the random assumption makes more significant difference from anchoring-behavior assumption when the end-customer demands are more variable.

Fourth, it is notable that the experimental data of this study shows a very strong demand-chasing behavioral tendency unlike those in other existing literatures. A plausible explanation might be that the subjects in our experiments are undergraduate students who have not been trained for newsvendor problems. Still, it does not cloud the fact that the information about retailers' behaviors improves the supplier's inventory decision, considering that neither the MBA who have learned the newsvendor model make optimal decisions nor the training improves the inventory decisions (Schweitzer and Cachon (2000)). What circumstances lead to retailers' demand-chasing tendencies can be an interesting topic for future research.

Lastly, the Bayesian regression analysis used to estimate model parameters in this study can be a new methodology for forecasting demand given the historical data. There are many ways to forecast demands, including subjective methods such as Delphi method and computational methods such as linear regression. Bayesian

regression is especially useful for individual-specific parameter estimation, even with small-size samples, and thus it would capture individual human behaviors effectively. As we only considered two behavioral tendencies (mean-anchoring and demand-chasing), there is still room for model improvement. There may be a better model that explains human newsvendors' behaviors well than Model B and searching for such a model merits another future study.

3.6. Conclusion

This chapter investigates whether a supplier can improve inventory decisions by incorporating retailers' behavioral tendencies into the decision making processes when the retailers make non-optimal inventory decisions under a repeated newsvendor setting. By Bayesian regression analysis with experimental data, we were able to estimate the demand distribution a supplier faces and thereby compute the supplier's possible cost savings. As a result, we observe a significant improvement in the supplier's inventory decision if she estimates the demand distribution with a model that captures the anchoring tendencies instead of assuming aggregate randomness. As the model selection relies much on the data, it is an important task to determine whether the retailers are mean-anchoring, demand-chasing, both, or neither. In addition, we observe that the information about retailers' behaviors is more beneficial for the supplier when the end-customer demands are more variable. It is certain that more precise information on the data (order history) will lead to a better inventory decision for suppliers. The information includes the retailers' behavioral tendencies, individual-specific order behaviors, and the variability of end-customer demands, etc.

This study contributes to behavioral operations management literatures by focusing on the behavioral effect on supply chain performance in newsvendor inventory decisions. Further, it could be a first step towards future research with huge potentials. First, it is important to find the best model that describes retailers' behaviors. There may be other behavioral tendencies than mean-anchoring and demand-chasing. Also, we can think of a reverse situation for sourcing decision. That is, if suppliers are irrational and a retailer is rational, the retailer might enhance the sourcing decision by understanding suppliers' non-optimal behavioral tendencies. As mentioned earlier, Bayesian regression analysis may serve as a useful methodology for demand forecasting, with its powerful capability to explain individual-specific data. Finally, we might consider the behavioral effect on supply chain performance for other operational problems not limited to newsvendor settings. For example, retailers may have a tendency to use more marketing promotions in certain selling seasons and suppliers may figure out retailers' such behaviors to facilitate their inventory decisions. In all cases, the managerial implication would be that understanding supply-chain partner's behaviors will improve the decision-making processes and that it is important to find a way for better understanding.

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